Healthcare Utilisation in Indonesia:
Determinants and Projections

Pungkas Bahjuri Ali

A thesis submitted for the degree of
Doctor of Philosophy of the Australian National University

February 2013

Declaration

Except where indicated, this thesis is my own work, undertaken as a scholar from 2009 to 2013 at the Australian Demographic and Social Research Institute, the Australian National University

Pungkas Bahjuri Ali
February 2013

Acknowledgement

I would like to express my sincere appreciation to the many people and parties who have been helpful during my study and my stay in Canberra.

My great appreciation goes to Prof. Peter McDonald, who, as the chair of the supervisory panel for my PhD project, has given me continuous supports and encouragement and spent his valuable time in advising me from the beginning. I also wish to extend my great appreciation to Prof. Terence H. Hull, my co-supervisor, who has provided me with extensive advice and discussion on various aspects of my research. Prof. Hull also gave me the chance to work on projects that both assisted me financially, and improved my skills in dealing with data. My thanks also go to Dr. Jeromey Temple, a member of the supervisory panel, who helped me with the modelling.

Many thanks to all of the academic and administrative staff members and fellow students at the Australian Demographic and Social Research Institute (ADSRI) for all their support and the provision of a very stimulating environment. Special thanks to my fellow cohort, Imma, Ruri, Suharti, Henri, Mulyadi, Hasnani, Barbara and Liz, for helping to create such a lively and enjoyable Coombs environment. My appreciation also goes to AusAid and the National Development Planning Agency (Bappenas), who gave me this opportunity to pursue my PhD degree at the Australian National University and to Elite Editing for the editorial advice.

My deepest gratitude goes to my lovely wife, Yogi, and my children, Bona, Indra and Tiara, for their unconditional love, support and understanding during our stay here in Canberra. To my humble parents, Rukiyah and the late L.W. Atmojo, who made all of this possible. *Rawe-rawe rantas, malang-malang putung.*

Abstract

This study explored the roles played by the demographic and non-demographic characteristics of users and provider's characteristics in determining outpatient healthcare utilisation in Indonesia, and simulated the effects of these demographic, health insurance subscription and chronic disease factors on outpatient healthcare utilisation in the future. The study is expected to contribute to public policy by providing empirical evidence of the determinants of healthcare utilisation in Indonesia, filling a gap in research of roles of provider characteristics, and providing insights into how to incorporate non-demographic factors into utilisation projections.

The study employed various statistical and mathematical tools, including discrete choice models for determinant analysis, cohort component methods for population projection and propensity methods for the projection of healthcare utilisation. Three main sets of data are used: the 2007 National Social Economic Survey (Susenas), the 2007 Indonesia Family Life Survey (IFLS) and the 2007 Basic Health Survey (Riskesdas). For the population projections, the base population is drawn from the post-enumeration-adjusted 2010 Population Census.

The study demonstrated that healthcare utilisation and choice of providers in Indonesia are determined by both demographic and non-demographic factors and, in general, this is in line with Andersen's behaviour framework of health service use. The study findings also support the notion that the effect of age on utilisation is not monotonic. The difference in association and the degree of influence of independent variables on the decision to visit and on choice of provider indicates that the decision to use healthcare and the decision to choose a provider is not simultaneous, but rather a two-stage process.

High price of service and low numbers of doctors deters the use of health services. Distance and drug availability are also associated with the choice of providers. Response to provider characteristics is not uniform, but varies across the population. This study also indicates the presence of a 'bypassing phenomenon', which occurs when patients bypass nearer healthcare providers to seek a higher-quality provider.

The size of the Indonesian population is projected to increase by 19.6% during 2010–2025. Due to this population growth, total healthcare utilisation is expected to increase by 25.7% over the same period, with the pattern of utilisation to follow the pattern of population increase. Compared to the effects of health insurance and chronic disease, demographic change will continue as the major driver of increased healthcare utilisation in the future. Further, for some age groups (for example, children and adult), the effect of health insurance and chronic disease will also be very significant.

In the policy context, the study indicates that income-related inequity in access to healthcare services will not be a significant issue; however, inequity in access to high-quality providers will. Access to healthcare among children and the elderly from lower social economic backgrounds is substantially lower than for other cohorts, and it was also found that urban dwellers are more sensitive to price of service and less sensitive to distance to healthcare providers, while rural dwellers are the opposite.

Table of Contents

List of Tables

List of Figures

List of Appendices

List of Abbreviations

ADSRI	Australian Demographic and Social Research Institute
AME	average marginal effect
ASDR	age-specific mortality rate
ASFR	age- specific fertility rate
CDR	crude death rate
CI	concentration index
GP	general practitioners
HFA	Health for All
ICBS	Indonesian Central Board of Statistics
IDHS	Indonesia Demographic and Health Survey
IFLS	Indonesia Family Life Survey
IIA	independent of irrelevant alternative
IMR	infant mortality rate
MDG	Millennium Development Goals
MNL	multinomial logit
MNP	multinomial probit
MoH	Ministry of Health
NHRDC	National Institute for Health Research and Development Centre
NL	nested multinomial logit
PES	Post Enumeration Survey
RPL	random parameter logit
SES	social economic status
Susenas	National Social and Economic Survey
TFR	total fertility rate
VIF	variance inflation factor
WHO	World Health Organization

Chapter 1
Healthcare Utilisation in Indonesia: Filling an Empty Space

In 2007, about one-third of the population in Indonesia experienced symptoms of sickness, such as fever, cough, headache and nausea, at least once a month. Indonesian people reported responding to these symptoms in various ways, with 45% seeking outpatient medical care from medical professionals. The remainder (55%) preferred to self-treat their illness, to use traditional medicines or even to forgo any healthcare treatment.

Explaining healthcare-seeking behaviour—that is, the decision to seek or not to seek medical care, and choice of provider—is a fascinating and complex subject that draws extensive research from diverse disciplines, such as health economy, epidemiology, sociology and physiology. As a result, many studies have investigated the monetised aspects of healthcare utilisation, healthcare utilisation related to specific diseases, and the underlying psychological, cultural and biological factors associating with the behaviour.

Demography has recently gaining importance in the study of healthcare utilisation for a number of reasons. First, there is a global consensus[1] on people's right to healthcare regardless of their place in the social structure of the community, and regardless of their ability to pay. Second, financial supports to reduce barriers to service, such as social health insurance, are widely practiced, resulted in a decline in the role of out of pocket expenditure (Getzen, 2004). Third, utilisation can be viewed as an individual behaviour (Andersen and Newman, 2005) that varies with demographic characteristics.

This study takes a demographic approach to explain variation in healthcare utilisation in Indonesia, by investigating the associations between outpatient healthcare utilisation

[1] Recently this has been reinstated in the Millennium Development Goals, which specify various health-related targets. For the Indonesia context, the right to healthcare is stipulated in article 28H verse (20) of the amended Indonesian Constitution.

and the broad demographics of the users (that is, their sex, age and social, economic and environmental conditions). This focus on user demographics reflects the demand side of the utilisation, which is only one-half of the analysis (Feldstein, 1996). Therefore, this study will also deal with the characteristics of supply (the other half of the analysis) to provide a more balance perspective of how healthcare utilisation is shaped.

Chosen as the case in this study, Indonesia has tremendous variations in healthcare utilisation among its different population groups. Further, significant population and economic growth, social change and epidemiological transition along with massive public interventions are expected to change the shape of healthcare utilisation in Indonesia in the future. These dynamics are not unique to Indonesia, and this study draws parallels with the situation in many other countries experiencing rapid population growth and social and economic changes, especially in the developing world. This study seeks to simulate the effects of demographic change on future healthcare utilization and compare them with the effects on non-demographic factors.

A. Local Policy Context

Overall, the health of the population is characterised by high maternal mortality, high infant mortality and a high death rate from both communicable and non-communicable diseases. Although the mortality rate has been reduced significantly in recent decades, the situation is still worrisome and will probably stand for many years to come.

There has been a long and continuing concern, primarily within the government and various civic organisations, over the general health status of the Indonesian population. Among the various factors associated with the health status of the population, access to healthcare service has attracted much attention for its mutability over a short period by various policy interventions. Subsequently, the central debate on the effort to improve population health lingers on healthcare service utilisation, which is further translated into health service delivery.

Various measures have been pursued by the government to improve healthcare utilisation. The 2010–2014 Medium Term Development Plan outlines the current policy direction, which seeks to improve access to and the quality of public health by providing adequate facilities and reducing the financial barriers to access of healthcare (Bappenas, 2010). One bold policy intervention, starting in the 1970s, has been the massive health infrastructure development to bring healthcare closer to users. Another has been the expansion of health insurance for the poor, leading to the current push to achieve universal coverage of health insurance by 2014.

Despite all efforts, until today, healthcare facilitates in Indonesia remain 'empty spaces.' There are still shortages in the number of medical doctors, equipment and quality services. In addition, many facilities suffer from patient 'shortages', shown by a low utilisation rate. In the last two decades, the proportion of the population seeking medical care has been lingering between only 35 to 45% of the total sick population.

Understanding of the underlying factors influencing healthcare utilisation in Indonesia based on empirical data has been lacking. Most situation analysis has relied on the normative sets of standards; that is, the evaluation of utilisation has been based on the standard of the medical need of the current demographic composition and medical practices. For example, in the 2009–2014 Strategic Plan of the Ministry of Health, the adequacy of the number of health professionals is measured by the ratio of health workers to population (number of physicians per 100,000 people). Although simple and straightforward, this does not necessarily reflect actual utilisation (Feldstein, 1996). The need might not translate into demand or, conversely, demand could exceed need.

Understanding demographic and social economic determinants of healthcare utilisation, and being able to predict or project its trajectory into the future, is necessary in formulating the right policy, especially in demographically, socially and economically ever-changing environments such as Indonesia.

B. Academic Research Context

There have been several studies on the determinants of healthcare utilisation in Indonesia based on data prior to 2000 (Hidayat and Pokhrel, 2009, Lance, 2003), especially on the effects of demographic, income and other social factors. The most recent studies using post-2000 data are those of Rokx et al. (2010) on user preference of healthcare providers, and Sparrow et al. (2010) and Erlyana et al. (2011) on the roles of social health insurance. However, these studies were not intended to explore the determinants of health care utilization, and thus little is known about the effects on healthcare utilisation of the demographic, social, economic and health needs of users and the characteristics of providers.

Research in health economics deals primarily with price of service, income level, value of time and health insurance. The effects of provider characteristics such as distance and service quality are more limited, mainly due to a lack of facility-based data that can be matched with user-based data. To circumvent the problem, the missing values of provider characteristics are imputed (Borah, 2006, Dor et al., 1987, Newhouse et al., 1974, Qian et al., 2009), although this method is prone to selection bias depending on the imputation method (Borah, 2006, Lance, 2003).

For future utilisation, there have been debates on the effects of ageing on future healthcare expenditure. Several studies have demonstrated that population ageing has significant financial consequences (Getzen, 2004, Henripin, 1994, Lee and Miller, 2002, Seshamani and Gray, 2004). However, others have found that the effect of population ageing is subtle and serves as a 'red herring' (Zweifel et al., 2004) diverting attention from technology, increase of income and social health insurance as the cause of growth of healthcare expenditure. Based on these latter studies, ageing will not significantly affect future healthcare expenditure (Burner et al., 1992, Cutler and Sheiner, 1998, Evans et al., 2001, Strunk and Ginsburg, 2002, Zweifel et al., 2004).

One of the assumptions that contribute to the dispute is the monotonic effect of age, which assumes that older people use more health services. Several studies have shown that the trajectory of utilisation is specific to age groups (Wolinsky et al., 1988), indicating the different trajectory during the life course. In countries with low fertility and mortality, the effect of ageing is expected to be low. In the United States (US) for example, Strunk et al. (2006) suggested that ageing contributes only 0.74% of annual growth of inpatient service in hospital. The small effect of ageing on healthcare expenditure is also evident in Canada (Evans and Williamson, 1978), Australia (Richardson and McKie, 1999), France (Dormont et al., 2006) and the international context (Gruber and Wise, 2001). The effect is small due to the gradual nature of ageing (Reinhardt, 2003), or it is overestimated by ignoring the role of proximity to death

(Werblow et al., 2007), gain in life expectancy (Fuchs, 1984) and compression of morbidity (Coory, 2004).

Healthcare utilisation can be projected with various degrees of complexity. Projecting aggregate demand for healthcare can be as simple as using past trends (see, for example, Kao and Tung, 1980). Other studies included the demographic component (size, age and sex) as the predictor, such as in Australia (Schofield and Earnest, 2006), Greece (Mouza, 2002) and Canada (Tate et al., 2005), and for international comparison (Gibbs et al., 2008).

In contrast, the role of non-demographic factors in future utilisation remains unexplored. Until now, attempts to incorporate both the demographic and non-demographic characteristics of populations in projection models have been rare. Indonesia potentially can serve a good example for this endeavour because Indonesia is undergoing population ageing, epidemiological transition, high growth of population and rapid social change (for example, in income and education), as well as sizeable policy interventions (for example, the push for comprehensive social health insurance).

C. Research Objectives and Contributions

The objective of this study is to investigate the determinants of healthcare utilisation in Indonesia, in particular for outpatient services, and to simulate the effects of these determinants on future healthcare utilisation. The main research questions are:

1. What determines outpatient healthcare utilisation in Indonesia?
2. What will the effects of demographic and non-demographic changes be on outpatient healthcare utilisation in the future?

There is ample literature on the demographic, social and economic determinants of health expenditure. In terms of healthcare utilisation, particularly outpatient visits, the studies are more limited. This research is expected to contribute to the body of knowledge on the nature and determinants of healthcare utilisation using Indonesian data as a case of developing countries. In doing so, this study recognises the different trajectory in utilisation among children, adults and the elderly.

This study is also expected to contribute to understanding the effects of provider characteristics such as cost, distance and quality of service. The use of a facility-based survey in the model avoids the imputation that was the practice of previous studies in the absence of facility-based data. This study employs a relatively new method in healthcare research, allowing the researcher to estimate the variation in people's responses to specific factors.

Another contribution of this study is in the projection of the future demand for healthcare. This study goes beyond demographic components (that is, age and sex differential) by simulating individual characteristics, which have rarely been taken into account in previous studies. To the best of the author's knowledge, this study is the first of its kind to simulate the effect of both demographic and non-demographic characteristics for the projection of healthcare utilisation.

As to the public health policy sphere, this study provides a deeper analysis on the underlying factors that shape demand for healthcare in Indonesia, and helps in explaining the interaction between supply and demand in shaping healthcare utilisation. Understanding the determinants of healthcare and their consequences for the future population helps in building an argument for further policy debates.

D. Organisation of the Thesis

Understanding the determinants of healthcare utilisation should be taken as a matter of importance in the context of public policy in Indonesia, where massive government interventions have yet to boost healthcare utilisation as expected. This view is shared in the research world, where demography is gaining importance in explaining variation in healthcare utilisation (see Chapter 1). The state of research in healthcare utilisation is further discussed in Chapter 2.

Since the thesis is developed using Indonesian data, the state of healthcare utilisation in Indonesia is described in Chapter 3. This chapter outlines the potential determinants of variation in healthcare utilisation from both the supply (that is, availability, quality and price) and user perspective (that is, demographic, social economic and health needs).

Two main measures are used to describe demand for healthcare: 1) healthcare utilisation, which indicates whether a person or population group seeks medical care when sick and, if making a visit, 2) which type of provider is chosen. The analysis of the determinants of healthcare utilisation and choice of provider is presented in Chapter 4 and Chapter 5, respectively. Chapter 6 is dedicated to analysing the role of provider characteristics in determining utilisation.

The projected population for 2010–2025, as the foundation to calculate future utilisation, is presented in Chapter 7. This is followed by an estimation of the effects of expected demographic changes on future healthcare utilisation (see Chapter 8). In addition, the extent of demographic effects on future utilisation is compared with the effects of non-demographic characteristics (that is, health insurance subscription and chronic disease rate). Based on the determinants analysis, population projection and projection of healthcare utilisation, the possible implications for public policy in Indonesia are systematically investigated in Chapter 9. Chapter 10 concludes the thesis.

The entire study comprises several different stages of research (determinant analysis, population projection and projection of healthcare utilisation), each of which employs very distinctive methodology. Therefore, the data sources and methodology to be employed in each analysis are discussed in the relevant chapters.

Two main measures are used to describe demand for healthcare: utilisation, which indicates whether a person or population [illegible] when sick and, if making a visit, to which type of provider [illegible] the determinants of healthcare utilisation and choice of provider [illegible] 4 and Chapter 5, respectively. Chapter 6 is dedicated to analysing the [illegible] characteristics in determining utilisation.

The projected population for 2010–2035, as the foundation for projecting future utilisation, is presented in Chapter 7. This is followed by an estimation of the effects of expected demographic changes on future healthcare utilisation [illegible]. In addition, the extent of demographic effects on future utilisation is compared to the effects of non-demographic changes such as health insurance coverage and chronic disease rates. Based on the demographic analysis, population projections and projection of healthcare utilisation, the possible implications for public policy in Indonesia are systematically investigated in Chapter 9. Chapter 10 contains conclusions.

The entire study comprises several different stages of research, encompassing analysis, population projections and projection of healthcare utilisation, each of which employs very distinctive methodology. Therefore, the data sources and methodologies employed in each analysis are discussed in the relevant chapters.

Chapter 2
The Dynamics of Demand for Healthcare

In every phase of life, a person's health is determined by biological imperatives, individual behaviour, social and economic status, environment, access to healthcare[2] services and a complex interaction among these factors. From an economic perspective, this interaction is formulated in a health production function, with all the determinants set as inputs (Folland et al., 2012). This function does not imply the dominant role of healthcare over other factors. In fact, several studies on the high population growth over the last 300 years argue that healthcare was not the major driver for the mortality decline that led to population growth prior to the twentieth century (Lee et al., 1997, McKeown, 1979, McKinlay and McKinlay, 1977).

Nowadays, in countries in which water, sanitation and nutrition have improved, the role of healthcare for population health has become more important than in previous decades (Folland et al., 2012, Fuchs, 1984). Subsequently, research on healthcare determinants has gained momentum, especially when it is associated with population dynamics and a sizeable change in individual behaviour and public interventions.

Studies on demand for healthcare have been carried out for various purposes within the framework of economy, epidemiology, social psychology and other approaches. Studies within economics are interested in the effects of price; while within social psychology, the focus is on the underlying behaviour driving the demand. Studies in the epidemiology area are motivated primarily by interest in clinical studies, such as on malaria and cardiovascular and cancer screening. Other studies on the demand for healthcare are more general and seek to identify the relationship between demand for healthcare and various factors at the individual, community or macro levels.

---

[2] The term 'healthcare' is often used interchangeably with 'medical care'. However, since medical care refers to the professional treatment of illness or injury, healthcare is used in this thesis to capture treatment by traditional healers as well. Such treatment is not part of formal health service provision in Indonesia, but is widely used by people when seeking care for their illness.

This chapter presents the foundation of demand for healthcare by exploring the concept and measurement of demand for healthcare, the theoretical frameworks for determinant analysis, projections of demand for healthcare, and studies on the demand for healthcare using Indonesian data.

A. Concept and Measurement

Demand is an economic concept that describes the quantity of a good or service per unit of time that an individual will purchase or consume given predetermined factors. It represents the quantity that an individual is willing and able to buy (ADB, 2000). Demand for healthcare is not necessarily the same as need for healthcare, which measures the level of necessary health service from a medical perspective (Feldstein, 1996). For example, an individual can have more demand than is medically required or, conversely, an individual can have less demand than is medically required.

Demand can be different from utilisation, which refers to the actual use of healthcare (ADB, 2000). For example, the number of individuals that would like to visit a healthcare provider (demand) might be greater than the number that can actually do so (utilisation). For others, the distinction between demand and utilisation of healthcare is not clear, or not important. Feldstein (1996), for example, uses demand and utilisation interchangeably. Both terms refer to the actual use of healthcare to differentiate them from need, which reflects standardised biological imperatives. Other studies also use the term 'demand for healthcare' to refer to healthcare provider choice and utilisation (Arendt, 2012, Borah, 2006, Hidayat and Pokhrel, 2009, Lance, 2003, Qian et al., 2009, Sahn et al., 2003).

There are several options in quantifying healthcare demand or utilisation, such as healthcare expenditure, length of stay for inpatient visits, number of visits for outpatient services, choice of providers and number of certain treatments for a specific disease. A common measure of healthcare demand or healthcare utilisation is healthcare expenditure, which measures the amount of money spent to pay the direct cost of treatment, or to have other healthcare services. Health expenditure has long been suggested as a measurement, as it reflects both the type and intensity of the treatment.

Health expenditure has been used primarily to investigate the effects of income shock, with the primary interest in its elasticity (Kao and Tung, 1980, Kong and Lee, 1999, Lee and Miller, 2002, Manning et al., 1987, Strunk et al., 2006).

However, healthcare expenditure measures a complex combination of price, quantity and quality of care (Folland et al., 2012). It can suffer from bias if not adjusted for price changes and changes in the product itself, such as the quality of services (Feldstein, 1966). The measure of price also poses a problem when health insurance or other subsidies exist that significantly lower the cost by users. Often, the amount of healthcare expenditure, especially for outpatient visits, is relatively low, such that its variability may not be sensitive to detect the effect of independent variables and may not be ideal for a determinant analysis.

Another measurement of healthcare utilisation is the quantity of contact between users and their healthcare providers (often termed 'visit rate'). This measure includes the number of visits for outpatient care or number of days treated for inpatient care. However, this measure does not necessarily reflect the intensity of care (Folland et al., 2012). The analysis of number of visits can be conducted at the individual or market level (aggregate demand). At the individual level, demand for healthcare is measured by the number of visits made by an individual. At market level, the measure is total number of visits made by a community or a group of population.

While earlier studies focused on the aggregate demand for healthcare, Akin et al.'s (1986) study, and many subsequent to it, used the family or individuals as decision-making units. The unit of analysis at this level usually requires more attention to individuals, households and environmental characteristics, which usually have tremendous cross-section variations (Lance, 2003, Rosenstock, 1966). Thus, this model can be complex in terms of number of variables and their interactions.

B. Approaches in the Study of Demand for Healthcare

Explaining the trend and variation of healthcare utilisation is not easy because it is influenced by both supply and demand. Analysis of supply is related to provider characteristics such as price, technology, legal barriers and regulation and the production of health workers. Demand analysis investigates the roles of demographic, social economic and other factors related to user characteristics. Therefore, in the study of healthcare, demand analysis only comprises one-half on the required analysis (Feldstein, 1996).

The utilisation of healthcare if often viewed as an individual behaviour (Andersen and Newman, 2005). However, individual behaviour itself is a function of individual characteristics, surrounding environment and societal forces, and the interactions between these components (Moore et al., 1972). Therefore, a study of demand for healthcare or utilisation can go beyond individual behaviour by including community, environment and health system characteristics (such as the quality of medicine and accessibility to healthcare providers).

McKinlay (1972) reviewed studies in health service use and mapped six analytically distinct approaches in the study of utilisation behaviour: economic, socio-demographic, geographic, social psychological, socio-cultural and organisational (also termed the 'delivery system' approach). Recently, the distinction between these approaches has become more subtle. Each can be used simultaneously in a model (see, for example, the behavioural model of health service utilisation developed by Aday and Andersen, 1974). McKinlay (1972) suggested that researchers should be more flexible in their approaches and let the inductive tendency characterise their work. It has also been suggested that researchers should engage more actively with baseline social-demographic information.

The following sub-sections briefly describe the most cited models for investigating demand for healthcare: the health belief model, the economic model and the behavioural model. These models deal primarily with the socio-demographic characteristics of users, the cost of service, environment and provider characteristics (that is, geographic factors and health system delivery capacity).

B.1. Health Belief Model

The health belief model is rooted in social psychology research and comes mainly from the work of Hochbaum (1958), Rosenstock (1966), Leventhal et al. (1960), Heinzelmann (1962) and Kegeles et al. (1965). This model describes constructs of perceived threats and benefits that represent perceived susceptibility, severity, benefits and barriers (Rosenstock et al., 1988). A person takes a specific health-related action toward positive change if he or she feels that a negative circumstance can be avoided, has a positive expectation to avoid it and believes that he or she can perform that action. Other modifying variables such as culture, education level, past experiences, skills and motivation were later introduced to the model.

The main limitation of this model is that it is based on attitude or belief rather than on behaviour or real actions. As such, researchers find it difficult to use this model to analyse healthcare utilisation, which reflects the real actions of behaviour. Moreover, it does not accommodate non-health-specific motives, such as price, which are common in healthcare utilisation studies. Thus, those studies that have sought to explain utilisation using this social-psychological concept are surrounded by unresolved and fundamental methodological issues (McKinlay, 1972).

Rosenstock (1966) expressed doubt as to the importance of belief. Further, the precise influence (if any) of belief on subsequent health behaviour is unclear (McKinlay, 1972). This has shifted researcher attention to the cue of actions; that is, the events, people or things that influence people to change their behaviour (for example, media campaigns). The perceived link between belief and cue of actions means that the health belief model is commonly used in health education and promotion. This model is used primarily in studies on preventive and sick-role behaviour, with only a few studies having used this model to investigate clinical utilisation (see Glanz et al., 2008).

B.2. Economic Model

The economic approach of demand for healthcare is based on utility maximisation theory. This theory holds that people maximise their utility by considering two groups of goods: health services and other goods. According to the conventional utility model, the demand for healthcare will fall with the price of care and rise with the price of most other goods and income (Folland et al., 2012).

The economic model of healthcare demand is primarily concerned with the primary variables of interest; that is, the financial cost of healthcare. Nevertheless, the economic approach is still beneficial, even if user healthcare fees are not a problem (for example, where free-of-charge public healthcare providers and health insurance are available). This is because indirect costs such as cost of travelling, opportunity cost of waiting and travel time and forgone earnings play potentially important roles in healthcare utilisation (Folland et al., 2012).

Price of service as the main component in the economic approach can be part of a bigger picture of healthcare utilisation, involving other non-economic determinants. Theodore (1968), as cited in McKinlay (1972), outlined four successive stages in the formulation of demand for healthcare: 1) physiological and psychological condition; 2) perception of condition; 3) willingness to manage condition through health services; and 4) ability to transform need into demand, with the fourth stage including economic factors. This implies that economic factors such as cost of service, income and health insurance are placed among other non-economic variables.

The most prominent model based on utility maximisation comes from Grossman (1972) which drew a clear distinction between health and healthcare services. Subsequently, numerous other models have been proposed within the economic framework, including in the work of Newhouse et al. (1974), which incorporated health insurance, and Heller (1982), which deals mostly with less developed country data. Later, works by Akin et al. (1986) and Gertler and Gaag (1990) focused more on provider choice instead of on health expenditure.

Akin et al. (1986), using data from the Bicol Region in the Philippines, was among the first to combine individual user level data and facility based data in determining factors influencing choice of providers. In doing so, they assigned income, price and distance to the provider to enter the model separately into each alternative of providers. This approach was later challenged by, among others, Gertler and Gaag (1990), who questioned the consistency of Akin's approach in separating income from the price of service with stable utility maximisation because income could differentiate the decision rule and have no role in the choice of provider. They suggested not separating income from pricing terms, allowing for a non-constant marginal rate of substitution of health for consumption (Lance, 2003).

Various studies soon followed, either adopting Akin's approach (Grobler and Stuart, 2007, Habtom and Ruys, 2007, Hidayat and Pokhrel, 2009, Lepine and Le Nestour, 2011) or that of Gertler and Gaag (Borah, 2006, Canaviri, 2007, Qian et al., 2009, Sahn et al., 2003) or by attempting to consolidate and explain the two approaches (Dow, 1995).

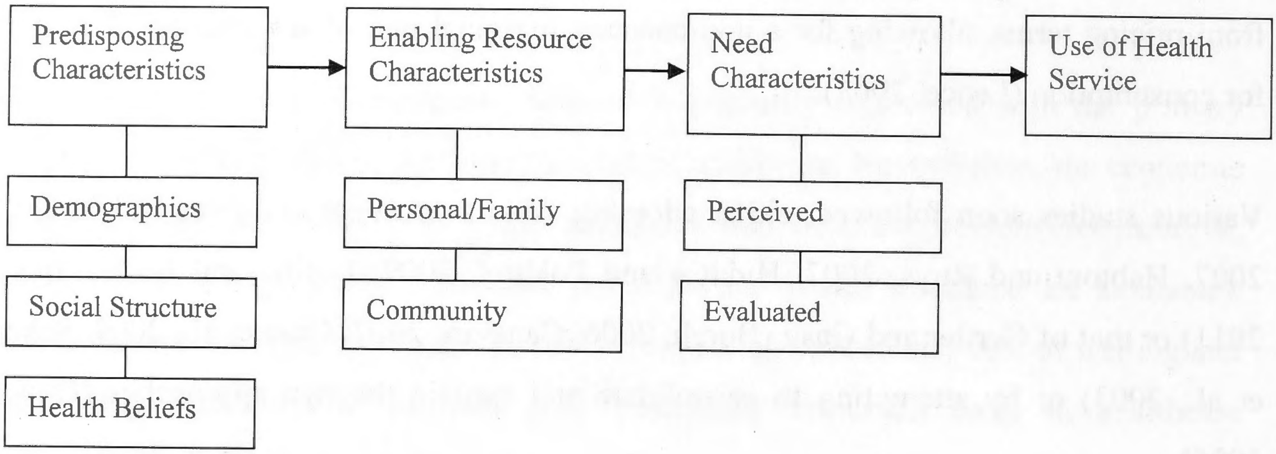
B.3. Behavioural Model of Health Service Use

Andersen (1995) developed a behavioural model of service use that mapped factors determining the use of health services. The model is one of the most cited, due to its broad range of factors that enable it to capture various interests in the study of demand for healthcare. The model has been used as the theoretical basis for many empirical studies of healthcare-seeking behaviour up to the present (Baldani et al., 2011, Fan et al., 2011, Hidayat and Pokhrel, 2009).

Although the model can incorporate comprehensive variables, it has been criticised as too broad and non-specific (Penchansky, 1976). At the other end of the spectrum, concerns have been raised that many important factors were overlooked, such as social network and culture (Guendelman, 1991, Portes et al., 1992) and organisational arrangement (Gilbert et al., 1993).

The model depicts three main factors of health service use: predisposing, enabling and need factors (see Figure 2.1). According to the model, the use of services is a function of predisposition to use services (demographic, social structure and health belief), factors that enable or impede use (income, health insurance, cost, accessibility) and individuals need for care (perceived and evaluated need). Andersen (1995) suggested that variation is primarily explained by need and demographic characteristics. In measuring outpatient care, all components enter the model because the conditions stimulating the use of services are less serious and demanding than for inpatient care.

Figure 2.1 Behaviour model of health service use (Andersen, 1995)



Demographic characteristics, such as age and sex, represent biological imperatives (Hulka and Wheat, 1985); social structure represents the place of the individual in the community, such as due to his or her education level, occupation and ethnicity; and health belief represents the attitudes and values of the person and the community. Later, other factors were incorporated into the model, including genetic (True et al., 1997) and psychological characteristics (DaVanzo, 1994, Rivnyak et al., 1989).

Enabling resource characteristics deal with access of people to health services at the individual, family or community level, and there is a requirement that these services are present for use to take place. This set of characteristics also measures the affordability of service use in terms of price, cost of service and forgone earnings. Individual and household income is thus a determinant of use of health services. Since the economic cost can be offset by health insurance, health insurance is also incorporated into the model (Mechanic, 1979).

The need for healthcare represents the immediate factor for health service utilisation. Need is measured by perceived or evaluated need, or both. Perceived need measures the view of individuals to their health status and functional state, while evaluated need is a judgment by health professionals based on physical examination and the need for care.

This model enables researchers to investigate the equity perspective of health service utilisation. Whitehead (1992) defines health inequity as differences in health that are unnecessary, avoidable, unfair and unjust. Inequity is explored by examining mutable factors that can be altered in a relatively short period to change utilisation patterns. The model also provides meaningful insight into the association of health service use to non-mutable or low-mutable factors such as demographic characteristics and social structure, and thus is helpful in projecting the effects of demographic change on demand for healthcare.

The behavioural model could serve for prediction or explanation (Andersen, 1995). Each component might be conceived of as making an independent contribution in the prediction. At the same time, the model suggests an explanatory process or causal ordering in which the predisposing factors might be exogenous (especially in the case of demographic characteristics and social structure).

B.4. Modelling Approaches

This section briefly reviews the modelling approaches commonly used in studies of healthcare utilisation, to lay a foundation for the more vigorous data analysis in the next chapter. This analysis will place emphasis on discrete choice analysis, which, according to Greene and Zhang (2003), can be explained in a probability model framework.

Estimating the demand for healthcare can be approached by various modelling techniques depending on the primary goal of the analysis and the type of data to be analysed. When the goal is to understand the system, a two-part model seems an appropriate choice because it can distinguish those factors affecting inclusion from those affecting the volume of the utilisation. For understanding the effects of individual covariates and prediction, a one-part model is recommended because it generates a single regression coefficient for each variable and can be interpreted easily (Diehr, 1999).

For discrete quantitative data, one of the earliest studies on healthcare utilisation was conducted by Akin et al. (1986) using multinomial logit (MNL) regression to investigate the demand for primary healthcare and adult outpatients in Bicol, the Philippines. Since then, MNL has been widely used in the study of choice of provider (Dong et al., 2008, Grobler and Stuart, 2007, Hidayat and Pokhrel, 2009, Lawson, 2004, Mwabu et al., 1993, Yip et al., 1998). MNL is used largely because it represents the natural decision problem faced by people when choosing a provider (Scott and Freese, 2006), as there are usually more than two alternatives of health facility within reach of individuals seeking care.

However, MNL is bound to the independent of irrelevant alternative (IIA) assumption (McFadden, 1986). The IIA assumes that the probability of an alternative chosen is independent of other alternatives. This property is not particularly appealing in consumer behaviour studies (Greene and Zhang, 2003). Therefore, if the IIA assumption does not hold, some other alternatives to relax the assumption need to be sought.

A natural alternative to MNL is the multinomial probit model (MNP). The MNP is different from MNL in the assumption of the distribution of the probabilities. MNL assumes logistic distribution, while the MNP assumes normal distributions. The immediate effect of choosing the MNP is the burden of the computational effort. However, with advances in numeric computing power, this distinction has become hardly noticeable. Further, both MNL and the MNP will provide similar conclusions (Greene and Zhang, 2003). Several studies of choice of provider have used the MNP (see, for example, Akin et al., 1995).

The next alternative to MNL is the nested multinomial logit model (NL). The NL requires a nesting structure that splits choices into groups (Cameron et al., 1988), thus allowing the variance to differ across groups, while simultaneously maintaining the IIA assumption within groups. In this model, a set of choices needs to be partitioned into branches or groups (Fuss and McFadden, 1978). In some cases, there is a natural partition of the choices to set into branches. In many other cases, however, partition is *ad hoc* and there remains no well-defined procedure to branch out the choices (Greene and Zhang, 2003). In such cases, the researcher sets the branches *a priori*.

NL has been used in several studies of healthcare provider choice. Gertler and Gaag (1990) were the earliest users of NL, using it to investigate the simultaneous effects of price and income. Other studies employing NL include Gupta et al. (2000) and Sahn et al. (2003), who categorised healthcare providers based on ownership; that is, private or public. Wiseman et al. (2008) used NL to test whether all Gambian healthcare providers exhibit the same properties, finding that the grouping was not necessary. Conditional logit is another extension of MNL that can be used to estimate the choice of providers, usually with an emphasis on the association with provider characteristics (see, for example, Klemick et al., 2009, Leonard et al., 2002).

Random parameter logit (RPL) is another variant of MNL. It is also called mixed logit (Revelt and Train, 1998). The model is different from MNL in that the coefficients of the estimate can be random, so it relaxes the IIA assumption and the presence of unobserved heterogeneity (Hensher and Greene, 2003). In MNL, the coefficient of the estimate is fixed (with its standard error). Consequently, it assumes that the trend or taste (as shown by the coefficient) to the choice or alternative does not vary across individuals. RPL specification, on the other hand, allows this coefficient to vary across the sample according to some distributions. A specific distribution function, such as normal, triangular, lognormal, uniform and other types of distribution function, can be imposed upon the distribution of the coefficient (Train and Sonnier, 2005).

RPL is regarded as the most promising state-of-the-art discrete choice model (Hensher and Greene, 2003). It has been adopted in various areas of study, including transportation, marketing and education. In health service utilisation, to the author's knowledge, only a few studies of demand for healthcare have used the RPL model (Audibert et al., 2011, Borah, 2006, Canaviri, 2007, Erlyana et al., 2011, Qian et al., 2009).

The use of the RPL model provides information not revealed by other models. For example, using MNL, MNP or NL, researchers can estimate the user's preference for each choice of provider. However, these models provide only the average preference of the sample population; they do not account for individual preference and thus do not reveal its distribution. The RPL model, on the other hand, can reveal those that reside on either side of the average value if the standard deviation is significant. For example, Borah's (2006) study revealed that a distance of more than 10 km to a health facility was disliked by 79% of the sample population, and favoured by the remainder (21%) of the sample population.

The logistic model is often used in the study of healthcare utilisation. However, the binomial nature of this model does not allow simultaneous choice of three or more providers. It is used more to investigate the decision to visit a healthcare provider as compared to an alternative, such as not visiting or self-treating (Fan et al., 2011, Lance, 2003). The logistic model is also used in the first stage of two-stage regression; where the first stage is the decision of whether to visit, and the second stage is choice of provider (Mihaylova et al., 2011, Wiseman et al., 2008). The obvious advantage of the logistic model is the simplicity of the model specification. The logistic model is often used to analyse equity issues among different demographic and social groups of population related to certain types of health service (see, for example, Baldani et al., 2011, Fan et al., 2011).

C. Projection of Demand for Healthcare

Projecting the demand for healthcare is difficult because it has to contend with various external variables and predict correlations between supply and demand (Hall et al., 1975). When healthcare demand is projected for the future population, the projection becomes more difficult and highly complex, as it involves population forecasting[3], which is also highly uncertain.

Many studies have attempted to forecast or project demand for healthcare into the future, usually by measuring health expenditure and number of total visits. Common approaches to forecasting and projecting demand for healthcare include mathematical extrapolations (such as moving average, regression), biological need for care and demographic-economic models, or structural modelling (Booth, 2006, Hall et al., 1975, Isserman, 1984). In practice, the distinction between methods is not always clear-cut. For example, extrapolation may introduce exogenous variables, while structural modelling may involve extrapolation. Within regressions, demographic and economic variables can also enter the model.

Mathematical extrapolations focus on regularities of pattern and extend this to the future without resorting to other exogenous variables. It is thus assumed that the pattern

[3] In this thesis, 'projection' is used differently from 'forecast'. A projection is a conditional statement about the future; that is, it is a calculation of numerical consequences, the underlying assumption of which is often referred to as an 'if then scenario'. Forecast refers to prediction, and a statement of the *most likely* future (Isserman, 1984). This distinction is loose, and these terms are often used interchangeably. However, the distinction is usually more profound among demographers, and this thesis adopts the distinction between forecast and projection.

underlying the values is a function of time (Booth, 2006). Time-series analysis and regression is a common tool for forecasting. Mathematical extrapolation has been used to forecast the demand for physicians (Scheffler et al., 2008), hospital use and cost (Lovell et al., 2009), monthly admission and patients days (Kao and Tung, 1980), health expenditure (Burner et al., 1992, O'Brien-Pallas et al., 2001), renal disease (Xue et al., 2001) and need for nurses (Cromwell et al., 1991).

Need-based projection is generally concerned with the quantity of certain health workers and has been widely used for planning purposes for its simplicity (Birch et al., 1994, Buske, 2007, Cromwell et al., 1991, Lee and Miller, 2002, O'Brien-Pallas et al., 2001). It is also widely used in projecting subacute care demand (Gibbs et al., 2008). This kind of projection is conducted by setting a standard of need for each group of population and then applying this normative standard to the future population. The limitation of need-based projection is that it might not reflect demand and does not take both macro- and micro-economic changes into account.

A structural modelling and demographic and social economic model can potentially be used in forecasting the healthcare demand of the future population. Until now, however, attempts to use structural modelling for forecasting have been very limited (see, for example, Watanabe and Tsubo, 1995). The model may have high descriptive power, but little predictive power (Booth, 2006). A study by Wolinsky (1981) using US data shows that except for age, family size, occupation and family income, predisposing, enabling and health needs provide an unstable structural relationship with the use of health services when they are compared longitudinally. This suggests that, in projecting future demand using a structural modelling approach, the effects of time should be taken into account.

A common method for demand for healthcare projection is the accounting (actuarial) method, the propensity model or a combination of these methods. The most common method is the construction of a model to analyse the propensity for healthcare utilisation according to current population demographic characteristics (age, sex or both), to then use these propensities as the basis to project the demand of the future population (Hall et al., 1975). This method can also be performed in a stochastic way. In the absence of stochastic processes, traditionally, the uncertainty of a projection is assessed by the development of various scenarios, with the typical choices of low, medium and high trajectories for each component of the forecast (Lee and Miller, 2002). There are numbers of studies within this category using the context of developed countries (Johnston and Teasdale, 1999, Lee and Miller, 2002, Mouza, 2002, Reinhardt, 2003, Schofield and Earnest, 2006, Strunk et al., 2006, Warren et al., 2008).

D. Studies on Demand for Healthcare in Indonesia

There have been various studies related to healthcare utilisation in Indonesia. One of the earliest studies is that of Chernichovsky and Meesook (1986), who investigated medical care visits, choice of providers and health expenditure using limited data drawn from the National Social Economic Survey (Susenas; in this case, 1978 Susenas). The study concluded that low income is a barrier to accessing modern healthcare, with the majority of care conducted at traditional providers and public facilities. However, the data and method used in this study did not accommodate a broad range of variables, including facility characteristics. Subsequent studies explored health expenditure and health insurance (Berman et al., 1987, Berman, 1989, Erlyana et al., 2011, Kruse et al., 2011, Musgrove et al., 2002, Rokx et al., 2009, Sparrow et al., 2010, van Doorslaer et al., 2007). Studies on visits to medical care providers are more limited (Gish et al., 1988, Hidayat and Pokhrel, 2009, Hidayat et al., 2004, Lance, 2003, Rokx et al., 2010, Sutrisna et al., 1993).

Although many studies have been conducted since the mid-1980s, the use of different settings, methods and data sources have made the longitudinal comparison of the effect of demographic and social economic change difficult. Further, a systematic analysis on provider attributes such as price, distance and quality of service has not been undertaken. Existing studies may also suffer bias due to utilising information from the household (for example, Berman et al., 1987) or because they do not interact with user characteristics (for example Rokx et al., 2010).

The following is a brief overview of the findings of studies by Lance (2003), Hidayat and Pokhrel (2009) and Rokx et al. (2010), which dealt with visits to and choice of provider, and are thus related to this study. Lance (2003) used the 1997 Indonesia Family Life Survey (IFLS) data as a case to assess the demand for healthcare in low-income nations. Hidayat et al. (2004) investigated the choice of provider using 1997 IFLS data, and Rokx et al. (2010) investigated health service utilisation in general, using 1997 and 2007 IFLS.

Lance (2003) defined demand for healthcare as the decision to seek medical care and the choice among healthcare providers. The study shows that consumer characteristics strongly influence health service utilisation. For example, sex, education, marital status and householder's status are significant factors in the decision to visit healthcare providers. For rural areas, price and drug availability, but not equipment in the health centre, are significant determinants of provider choice. Travel distance is also a significant factor in choosing healthcare provider. However, the effect of provider's characteristics depends on the user's age, sex and socio-economic status. For those living in urban areas, the effects of price and equipment are statistically significant, but not so for drug availability. However, these results may suffer from selection bias, since the information on price of service and travel distance is derived only from the facilities that are visited by the household as opposed to all facilities.

Hidayat (2008) explored the effects of sickness conditionality on the demand for outpatient visits in Indonesia. The aim of the study was to investigate whether conditional estimates in the IFLS data suffer from selection bias, as indicated by previous studies elsewhere (Akin et al., 1986, Dow, 1995, Hidayat et al., 2004). Using the MNL model, the study conducted two separate estimations: the first with the condition of being ill, and the second without that condition. Hidayat found that conditional estimates do not suffer from statistical selection bias.

Rokx et al. (2010) explored variations of health service utilisation between 1997 and 2007 using 2007 Susenas, with a focus on outpatient and inpatient visits. The results show that between 1997 and 2007, the usage rate of outpatient services rose from 20.5% to 23%, while inpatient services rose from 2.2% to 3.3%. The largest increase in overall utilisation was among the lowest quintiles. Yet, the population that forewent any treatment also increased from 23% to 27% during the same period. Further results show that utilisation was positively associated with household income and higher education level. Poor groups were more likely to choose public providers, while the more affluent groups (especially those in urban areas) tended to choose private providers.

income groups. Sparrow et al. (2004) investigated the ... IFLS data and Soksumul (2005) investigated ... using 1997 and 2000 IFLS ...

Lance (2003) defined demand for healthcare as the ... the choice among healthcare providers. The study shows that ... strongly influence health service utilisation. For example, ... and householder's status are significant factors in the decision ... providers. For rural areas, price and drug availability, but not ... centre, are significant determinants of provider choice. ... significant factor in choosing healthcare providers. However, the ... characteristics depends on the user's age, sex and socio-economic status ... living in urban areas, the effects of price and equipment are ... not so for drug availability. However, these results may suffer ... the information on price of service and travel distance is derived only from ... that are visited by the household as opposed to all facilities.

Hidayat (2008) explored the effects of sickness conditioning ... outpatient visits in Indonesia. The aim of the study was ... conditional estimates in the IFLS data suffer from selection ... previous studies elsewhere (Akin et al., 1998; Dow, 1995; ... the MNL model, the study conducted two separate ... condition of being ill, and the second without ... conditional estimates do not suffer from statistical selection ...

Kokx et al. (2010) explored trends of ... 2007 using 2007 Susenas, which focus on ... show that between 1997 and 2007, the ... to 23%, while inpatient services rose from ... utilisation was among the lowest quintiles, ... treatment also increased from 28% to 27% ... that utilisation was positively associated with ... level. Poor groups were more likely to choose ... groups (especially those in urban areas) ...

Chapter 3
Healthcare Utilisation in Indonesia

This chapter discusses the state of, and trends in, healthcare utilisation in Indonesia. From a public policy perspective, the health system plays a partial yet firm role in shaping healthcare utilisation. Therefore, health system performance in Indonesia will be briefly described first, to provide a context in which the dynamic of healthcare utilisation takes place. Considering the complexity of the health system, this chapter focuses only on the quantity, quality and accessibility of healthcare providers, including the adequacy of health workers. The subsequent section provides an overview of healthcare utilisation, as represented by the trends in utilisation rate and choice of provider.

This chapter emphasises the idea that variability in healthcare utilisation in Indonesia exists across time, region and the demographic characteristics of the users. The exploration of the links between healthcare utilisation and other characteristics such as social economics, living environment and health needs is brief in this chapter, with more in-depth discussion left for those later chapters dealing with healthcare utilisation and provider choice.

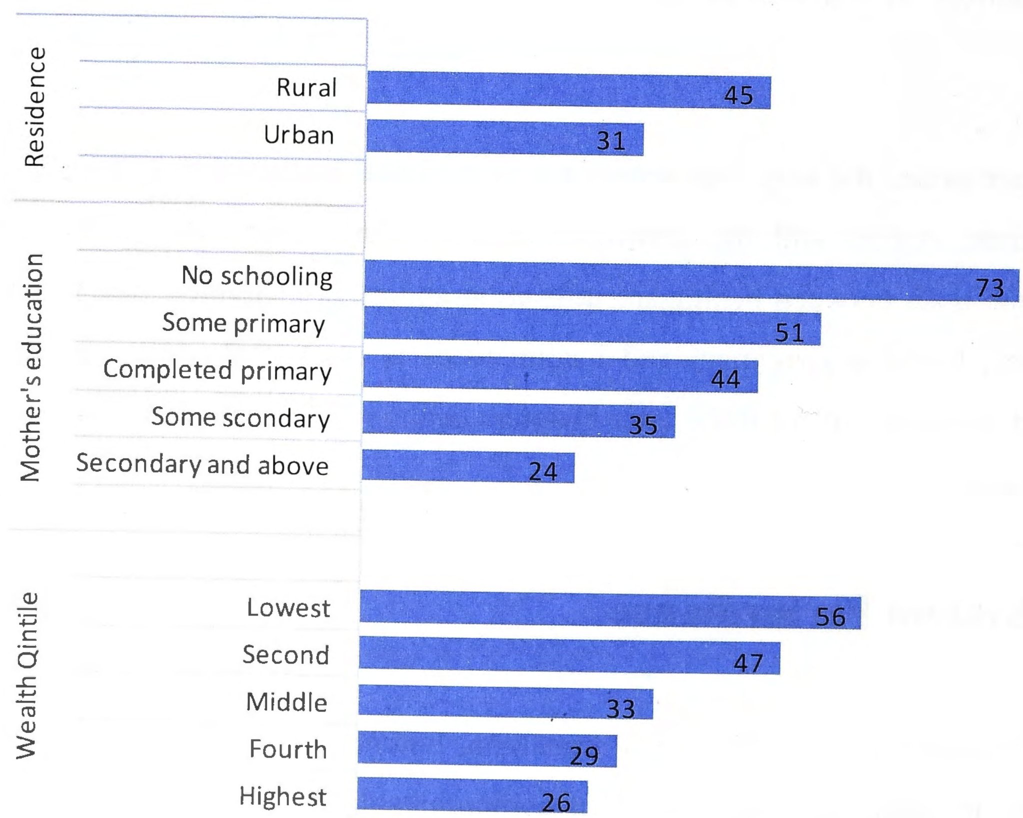
A. Health System Performance

According to the theory of epidemiological transition, Indonesia is in an epidemiologic transition phase, in which the contribution of communicable diseases as the cause of death is decreasing to be gradually replaced by degenerative and manmade diseases (Barrett et al., 1998, Omran, 1971). The contribution of communicable diseases to total death (all ages) has decreased from 44.2% in 1995 to 28.1% in 2007 (NIHRD, 2007). At the same time, the non-communicable disease contribution to total deaths has increased from 41.7% to 59.5%. This transition placed stroke and hypertension in the first and third rank of causes of deaths in 2007.

Despite being on the decrease, communicable diseases remain widespread and are a cause of major health problems in Indonesia. Tuberculosis was the second main cause of death in 2007. Other major communicable diseases in Indonesia include malaria, typhoid, pneumonia and dengue fever. Deaths due to prenatal and maternal disorder are also prevalence. In 2007, for example, there were 34 infant deaths per 1,000 live births and 228 maternal deaths per 100,000 live births (BPS and Macro International, 2008). This is close to the average infant and maternal mortality rate in Southeast Asia.

The difference in health status is apparent among the different groups of population. For instance, the infant mortality rate (IMR) is much higher in rural areas, among low educated mothers, and among the poorest households (see Figure 3.1).

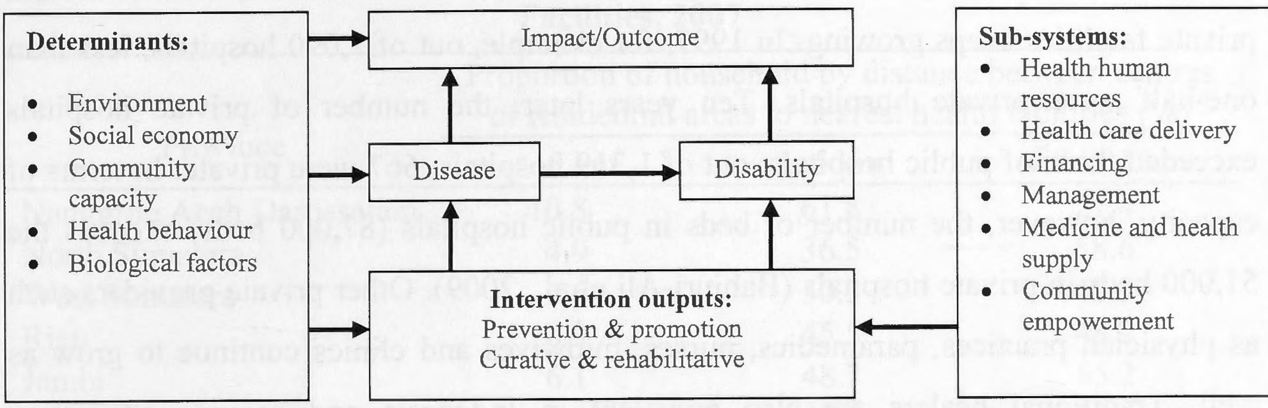
Figure 3.1 Infant mortality rate (death per 1,000 live births) by geographic and social economic characteristics, Indonesia 2007



Data source: 2007 IHDS

The Indonesian health system is intended primarily to tackle the problem of low health status and the high disparities among groups of population. The health system is revisited and adjusted regularly in response to emerging situations such as political superstructures, epidemiology and social and economic development. The health system is built upon six pillars: healthcare delivery, human resources for health, health financing, medicine and health supply, community empowerment and health management (MoH, 2004).

Figure 3.2 Framework of the Indonesian health system



Source: Bahjuri-Ali et al., 2009

All sub-systems are supportive in achieving improved health status through prevention and promotion, as well as curative and rehabilitative interventions. Outpatient services are a major part of these healthcare interventions and play an important role in the health system. The interest of this chapter is particularly on human resources for health, healthcare delivery and medicine and health supply, as these factors are closely related to the accessibility, affordability and quality of healthcare services.

A.1. Adequacy and Accessibility of Healthcare Services

Since the commencement of the first Five-Year Development Plan in 1968 and then the adoption of the Alma Ata Declaration in 1978, there have been massive physical constructions of primary healthcare facilities. As a result, by 2007 there were about 8,234 functioning health centres, 22,347 auxiliary health centres and 1,319 hospitals across Indonesia (Bappenas, 2008). Prior to 2000, the health system also benefited from extensive community-based health provisions, such as *Posyandu* (integrated service post), village maternity posts and village medicine posts, which provided health and nutrition promotion and services.

After 2001, health infrastructure development continued to progress, but at a lower speed. Due to government reforms, health sector policy has been largely decentralised to district authorities. The construction of public healthcare facilities can only take place in less developed or remote regions, along the country's border areas or in breakaway districts[4] (Bappenas, 2010).

While the construction of public infrastructure tends to slow down, the number of private facilities keeps growing. In 1997, for example, out of 1,090 hospitals, less than one-half were private hospitals. Ten years later, the number of private hospitals exceeded those of public hospitals: out of 1,319 hospitals, 667 were private. In terms of capacity, however, the number of beds in public hospitals (87,000 beds) exceeds the 51,000 beds in private hospitals (Bahjuri-Ali et al., 2009). Other private providers such as physician practices, paramedics, nurses, midwives and clinics continue to grow as well. Traditional healers are also prevalent in Indonesia and provide alternative treatments of illness for both the poor and the rich.

On average, one public health centre serves about 30,000 people.[5] According to health needs standards, the current level of primary healthcare provision in Indonesia is adequate. Thus, the government has largely ceased building new primary healthcare facilities. However, the national average conceals variations among geographically diverse areas. In low-density areas, access to health facilities is relatively more difficult due to geographical and transportation problems. Similarly, people living in remote areas, small islands and along the country's borders experience difficulties in accessing healthcare facilities. The government responds to geographical imbalances by having the discretion to continue construction of new health centres and public hospitals in these areas. With this policy, it is expected that the number of health centres will continue to increase slowly, reaching 9,000 units in 2014 (MoH, 2010).

In relation to the geographical challenges, Table 3.1 shows that significant proportions of the population live far from health facilities and hence potentially have difficulties in accessing those facilities. Variation among provinces is also apparent. At national average, 6% of households are living 5 kilometres or more from their nearest health

[4] 'Breakaway district' is a term referring to a newly created district because of the division of an original district into two or more districts/cities, resulting in an increase in the total number of districts. According to BPS, the number of districts/cities increased from 416 in June 2003 to 497 in June 2012.

[5] See the WHO website, Available: http://ino.searo.who.int/EN/Section3_24.htm [Accessed 9 May 2012].

facility. This figure can be as high as 16.3% in West Kalimantan and as low as 0% in DKI Jakarta, where most of the households are living within 1 kilometre of the nearest health facility.

Table 3.1 Proportion of Households Living within a Certain Distance of Health Facilities, 2007

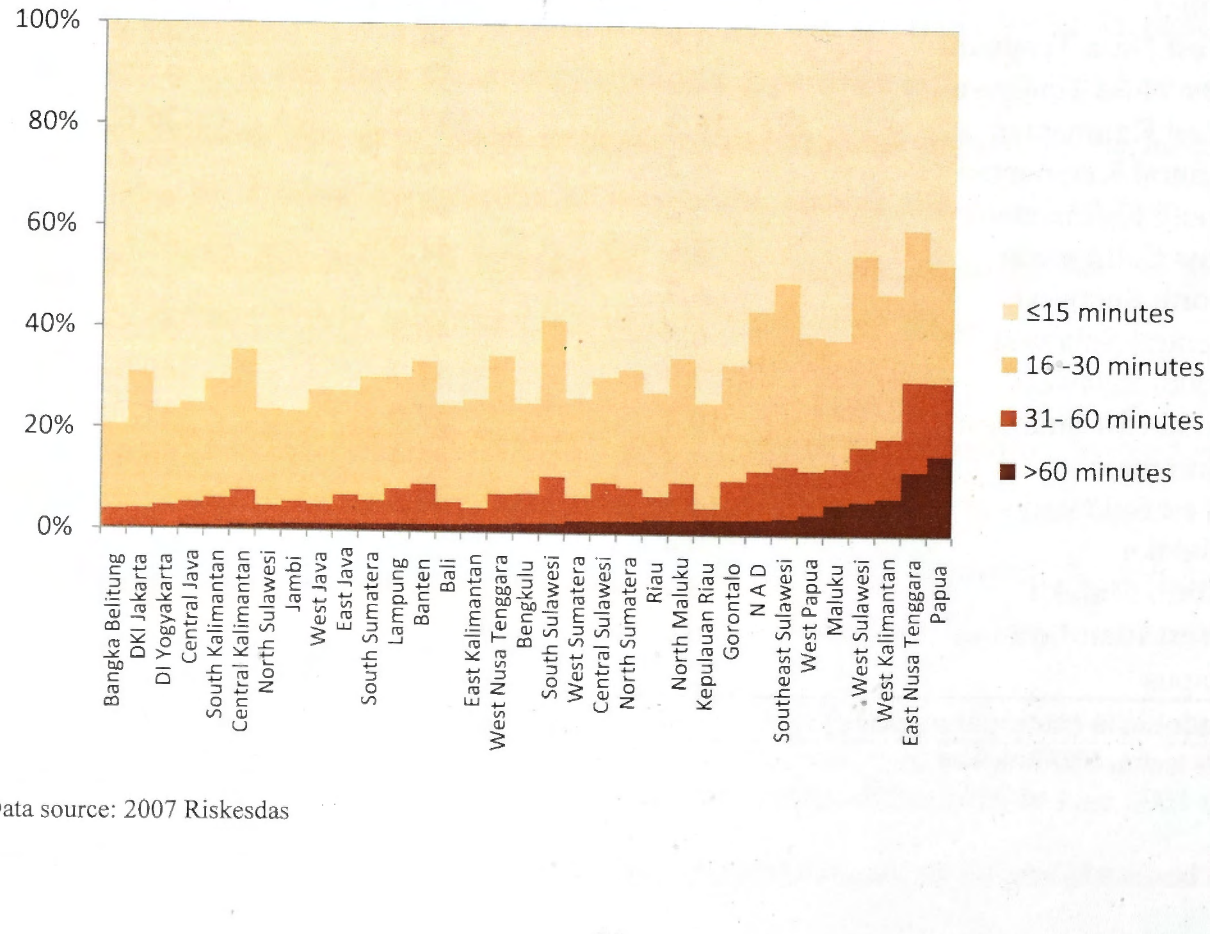
Province	Proportion of household by distance between centres of residential areas to nearest health facilities (%)		
	> 5 km	1–5 km	within 1 km
Nanggroe Aceh Darussalam	10.8	61.8	27.4
North Sumatera	4.9	36.5	58.6
West Sumatera	6.6	50.5	42.9
Riau	6.3	45.5	48.2
Jambi	6.1	48.7	45.2
South Sumatera	5.0	44.5	50.4
Bengkulu	4.4	43.0	52.6
Lampung	4.4	54.8	40.8
Bangka Belitung	7.3	37.6	55.1
Riau Island	2.7	42.0	48.2
DKI Jakarta	0.0	42.0	58.0
West Java	3.7	48.2	48.1
Central Java	2.0	46.6	51.4
DI Yogyakarta	2.3	50.2	47.4
East Java	3.4	48.9	47.7
Banten	7.5	44.6	47.9
Bali	3.5	47.0	49.5
West Nusa Tenggara	3.8	54.1	44.9
East Nusa Tenggara	14.2	54.1	31.7
West Kalimantan	16.3	47.2	36.6
Central Kalimantan	5.2	39.4	55.4
South Kalimantan	5.2	44.3	50.5
East Kalimantan	5.6	41.9	52.6
North Sulawesi	6.7	35.7	57.7
Central Sulawesi	6.8	40.8	52.5
South Sulawesi	7.9	52.3	40.0
Southeast Sulawesi	10.4	52.0	37.7
Gorontalo	7.3	54.4	38.4
West Sulawesi	14.5	47.6	37.9
Maluku	10.4	31.0	58.6
North Maluku	8.1	27.5	58.6
West Irian Jaya	6.6	35.7	42.9
Papua	12.7	45.7	41.6
Indonesia (national average)	6.0	46.4	47.6

Data source: 2007 Riskesdas

Data from 2007 Riskesdas shows variability of access to healthcare providers among regions and social economic groups. About 58.8% of households in urban areas reside within 1 kilometre of their nearest healthcare providers (hospitals, health centres, subsidiary health centres, physician practices and midwife practices), compared to 40.6% of households of rural areas. Accessibility is also related to social economic status: 53.8% of the richest quintile group resides within 1 kilometre of health facilities, compared to 43.8% of the poorest.

Within the notion of accessibility, travel time to health facility shows a significant variation among provinces (see Figure 3.3). Travel time reflects not only the spatial distance but also the availability of means of transportation and geographical obstacles. Generally speaking, people living in provinces on Java/Bali have shorter travel time to health facilities compared to people living in provinces outside Java/Bali, particularly in Eastern Indonesia (Papua, East Nusa Tenggara, Maluku, North Maluku and West Papua) and provinces with low population densities, such as West Kalimantan, West Sulawesi.

Figure 3.3 Proportion of households living within a certain travel time of health facilities, by province, 2007

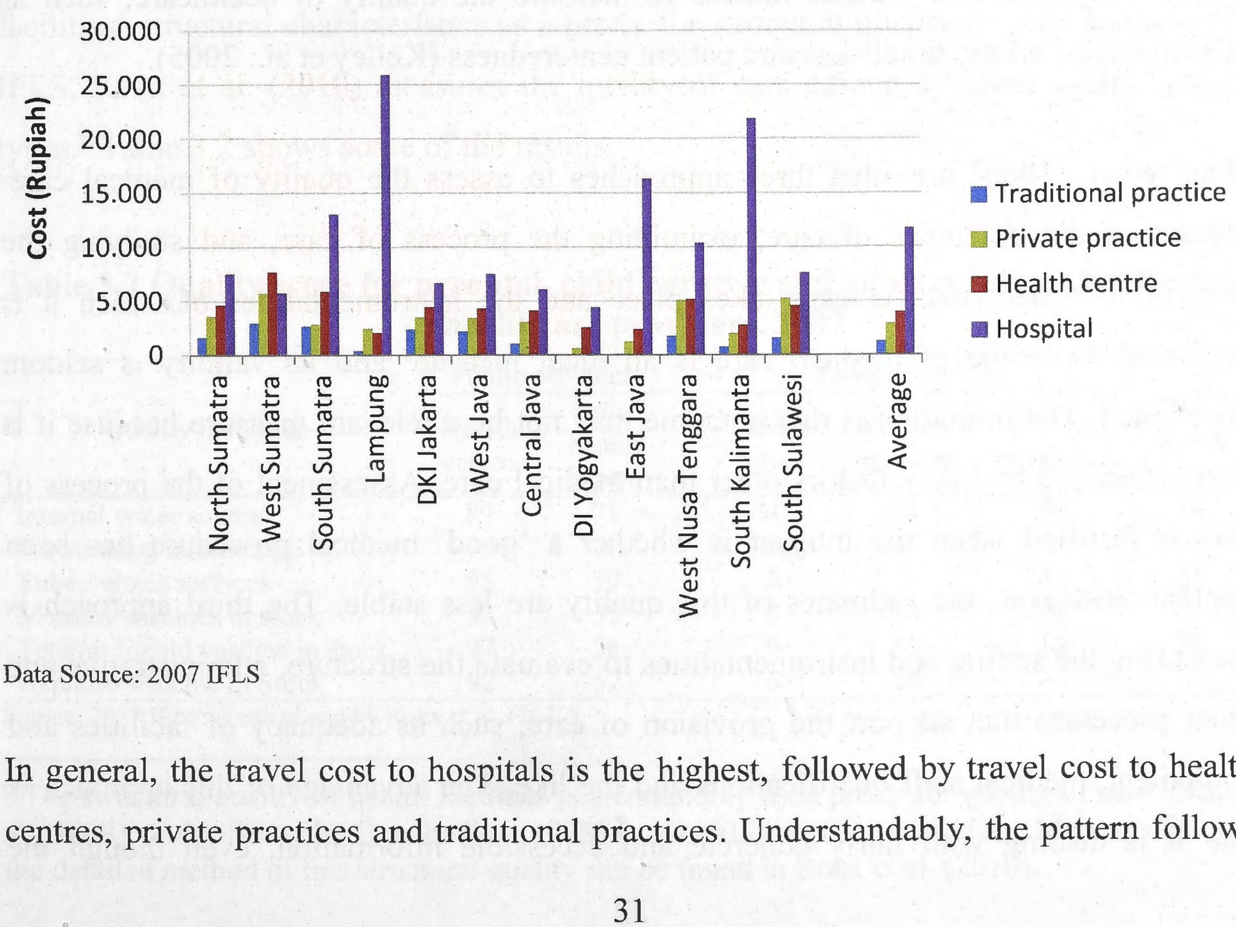


Data source: 2007 Riskesdas

That distance and transportation act as barriers to accessing healthcare providers can be observed in the 2007 Indonesia Demographic and Health Survey (IDHS), which indicates that among ever married women, at least 41% of them reported having at least one problem in accessing healthcare. The most reported problems were related to financial resources (25%), distance to health facilities (15%) or having to take transport (13%) (BPS and Macro International, 2008). However, these data are not sufficient to evaluate the effects of distance and travel time on utilisation, as they do not reflect the revealed preference as a measure of actual utilisation.

There is a lack of survey data on the cost of travel from household residences to available surrounding health facilities that can be linked to actual healthcare utilisation. The only available data is IFLS, which recorded travel characteristics (travel, cost, time of travel) from household to the office of the village head to nearest health facilities at the community level. The limitation of the data is that it covers only 18 out of 33 provinces in Indonesia, most of which are relatively developed regions, and does not cover provinces that are considered as having sparse health facilities such as provinces in Eastern Indonesia. Further discussion on accessibility is covered in Chapter 7.

Figure 3.4 The province average of travel cost from residential area to health facilities by type of health facility, Indonesia 2007



Data Source: 2007 IFLS

In general, the travel cost to hospitals is the highest, followed by travel cost to health centres, private practices and traditional practices. Understandably, the pattern follows administrative assignment of the health facilities. Hospitals and health centres are mostly available in the capitals of districts and subdistricts, respectively, and consequently their cost of travel is high. Meanwhile, private practices and traditional healers are not constrained by administrative level, so they tend to be located close to residential areas.

As previously indicated in 2007 IDHS, high travel cost and long travel time, *ceteris paribus,* may deter people from choosing health facilities, in the same fashion as distance influences healthcare utilisation. However, the extent to which travel cost is associated with the decision to seek care and with the choice of providers in Indonesia is largely unknown.

A.2. Quality of Care

There are various definitions of quality of care, such as 'doing the right thing at the right time in the right way for the right persons and having the best results possible' (Kelley et al., 2005), or the definition of the Institute of Medicine: 'the degree to which health services for individuals and populations increase the likelihood of desired health outcomes and are consistent with current professional knowledge (Chassin and Galvin, 1998). There are also various indices to measure the quality of healthcare, such as effectiveness, safety, timeliness and patient centeredness (Kelley et al., 2005).

Donabedian (1966) provided three approaches to assess the quality of medical care: measuring the outcomes of care, examining the process of care, and studying the settings in which medical care takes place and the instrumentalities of which it is produced. Outcome of medical care is an ideal measure and its validity is seldom questioned. The limitation is that outcome may not be a relevant measure because it is also influenced by many factors other than medical care. Assessment of the process of care is justified when the interest is whether a 'good' medical procedure has been applied. However, the estimates of this quality are less stable. The third approach is measuring the setting and instrumentalities to evaluate the structure, administrative and other processes that support the provision of care, such as adequacy of facilities and equipment, medical staff qualifications and the like. The advantage of this approach is that it is dealing with fairly concrete and accessible information, even though the relationship between structure and process or structure and outcome is often not well established.

In this section, the discussion on the quality of care adopts the third approach; that is, exploring the structural quality of medical care in Indonesia. In addition to the lack of relevance and stability of the first and the second approaches as discussed by Donabedian (1966), the reason for using the third approach is that determining indicators to evaluate the representative outcomes and processes of care is extremely difficult when the purpose is to examine its relationship with general healthcare utilisation for outpatient services. The appropriate outcomes and process effectiveness of care is highly dependent on the type of care sought by patients.

Another reason is that there is a lack of empirical data on the outcomes and processes of medical care, such as from a large-scale survey. Most of the available data are about health facility characteristics, such as availability of staff, equipment and medicine. These factors may have an association with the quality of health facilities, with the assumption that given the proper settings and instrumentalities, good medical care will follow (Donabedian, 1966).

One method to evaluate the quality of care is by constructing an index using health facilities' structural characteristics as a proxy for structural quality of care. Using 2007 IFLS, Rokx et al. (2010) measures the quality of care among different health facility types.[6] Table 3.2 shows some of the results.

Table 3.2 Quality score for prenatal, child curative and adult curative care by type of healthcare providers, 2007

Quality measures	Public provider		Private providers			
	Health centre	Sub-health centre	Private nurse	Private midwife	Private physician	All setting
Internal water source	89	71	80	84	89	84
Functioning microscope	79	5	1	3	7	25
Tuberculosis services	95	30	8	2	44	38
Measles vaccines in stock	97	51	5	48	11	51
Tetanus toxoid vaccine in stock	97	55	9	59	12	55
Hepatitis vaccine in Stock	92	52	6	54	16	52

Source: 2007 IFLS as calculated by Rokx et al. (2010)

[6] The structural quality of health facilities is a commonly used proxy for quality of care (Das et al., 2008), and reflects the Donabedian (1978) structural dimension of quality. More results and the detailed method of this structural quality can be found in Rokx et al. (2010).

Table 3.2 shows the score of some indicators of quality of equipment of healthcare providers, with higher scores representing higher quality. Overall, health centres have better equipment and a better drug and vaccine supply than do other facilities. This high quality score for health centres is understandable, as health centres have been designed as the frontier of public health for the majority of the population. Scores for the ability to diagnose, which is categorised as process of care quality, are similar across the types of provider, with the exception of private midwives, who have lower scores for child and adult curative care (Barber et al., 2007, Rokx et al., 2010). Chapter 9 discusses the process of care quality in more detail.

As for drug availability, in 2006 it is estimated that the pharmaceutical market in Indonesia was valued at USD 2.4 billion. This gives a per capita consumption of pharmaceuticals of USD 12. This figure is low compared to some neighbouring countries such as Malaysia and Thailand, partly due to the Indonesian government policy of support for low-priced generic medicine. Still, the pharmaceutical market has been growing at approximately 10% a year (Rokx et al., 2009).

The availability of medicine in public care facilities in Indonesia appears to be adequate, even though temporary shortages are sometime apparent. The availability of vaccines is sometimes hampered by the limitation of adequate storage facilities in less developed areas, which are often interrupted with electricity shortages. The availability of drugs at the district warehouses is also encouraging. However, there are problems with the high cost of inventory at multiple levels, date-expired products, and overstock and stock-outs at public facilities (Rokx et al., 2009).

Medicine can be accessed by the population through chemists and drug stores or even in the open marketplace. In 2007, the estimated number of chemists was 8,300 and the number of drug stores was 6,600. Medicine is relatively easy to obtain everywhere, especially in urban areas, and it is available directly from medical workers. The Indonesia Pharmaceutical Association estimated that only 30% of drug prescriptions are obtained from doctors, nurses and midwives (Bahjuri-Ali et al., 2009). Medicine is also accessible illegally on the black market. The World Bank estimated that in Indonesia, the penetration of sub-standard and counterfeit drugs could be as high as 25% of the market. This mostly affects the poor, who cannot afford to buy from formal sellers (World Bank, 2008).

Satisfaction with the service is one of the dimensions to measure quality (Donabedian, 1966). Satisfaction is regarded as an indicator of the responsiveness of the healthcare service to patient need, which has been included as one of the objectives of the national health system (Bahjuri-Ali et al., 2009, MoH, 2010). In this sense, responsiveness may be regarded as both a process and outcome measure of healthcare services. Table 3.3 indicates the variations in the populations' perceptions of healthcare responsiveness.

Table 3.3 Perception of users on responsiveness of outpatient services, 2007

	Percentage of household giving 'good' rating to the last health facility visited, by responsiveness indicators				
	Waiting time	Hospitality	Confidentiality	Information clarity	Room cleanliness
Total sample					
Average	86.8	90.4	87.5	87.2	85.1
Maximum (province level)	92.3	98.3	95.5	95.9	96.1
Minimum (province level)	67.6	73.2	69.3	67.3	65.9
Region					
Urban	85.2	90.0	88.1	87.7	86.6
Rural	87.6	90.5	87.1	86.9	84.3
Social economic strata					
Quintile 1 (poorest)	86.1	89.5	86.4	86.1	84.0
Quintile 2	86.0	89.6	86.5	86.3	84.4
Quintile 3	86.8	90.3	87.1	86.9	84.9
Quintile 4	87.1	90.9	87.9	87.8	85.6
Quintile 5 (richest)	87.7	91.4	89.1	88.7	86.7

Data source: 2007 Riskesdas

In general, it seems that there is little variation in the percentage of outpatients expressing their satisfaction with healthcare services (by rating the service as 'good') between various groups of outpatient living in urban and outpatient living in rural areas, as well as outpatients from different social economic strata. However, this measure may be subject to a selection bias (for example, a richer person might choose a better health facility) and is influenced by the demographic characteristics of the patients.

A.3. Health Workforce

The World Health Organization (WHO) defines health workers as those people engaged in actions with primary intent to enhance health (WHO, 2006). This broad definition includes unpaid carers, such as parents looking after their sick children, as health workers. However, data for health workers in most cases cover only paid workers in the healthcare delivery system. In this study, the discussion on the health workforce is limited to medical professionals working in the main health facilities and delivery points, and does not include administrative staff, workers for supporting activities or unpaid workers (and hence the term 'health workforce' and 'health professionals' will be used interchangeably in the remaining thesis). In particular, this study will focus on physicians, nurses and midwives.

Health professionals play an important role in primary healthcare in Indonesia, and the government has tried in various ways to increase their quantity continuously. As a result, in 2006 there were more than 68,227 medical doctors (general practitioners/GPs, specialist and dentists), 79,152 midwives and 308,396 nurses. This brings the ratio of health professionals per 100,000 population to 19.9, 35.4 and 137.9 for GPs, nurses and midwives, respectively (Bappenas, 2008).

The WHO uses international data to look for a threshold under which the package of essential interventions to achieve the Millennium Development Goals is unlikely to be met. The result suggested that an average of at least 2.25 health professionals (counting only doctors, nurses and midwives) per 1,000 population are needed to achieve 80% target coverage of delivery by health professionals. Using this threshold, Indonesia is categorised among countries with a critical shortage of healthcare professionals, as there were only 1.99 healthcare professionals per 1,000 population in 2007.

The Ministry of Health (MoH) uses health need sufficiency to set its national targets for the ideal number of health workforce to be achieved by 2010. For example, in each health centre, there should be at least two general practitioners (GPs).[7] In 2007, the average number of GPs per health centre in Java and Bali was 1.96, and 1.62 on other islands. The figure in urban areas is 2.04, compared to 1.58 GPs per health centre in

[7] This standard was calculated based on the Daftar Susunan Pegawai (the list of required workers) method for health centers, as stated in the Ministry of Health's Decree No. 81/2004.

rural areas (Rokx et al., 2010). Referring to 2010 targets, there is a big gap to fill in number of health professionals (see Table 3.4).

Table 3.4 Availability of health professionals in 2006 and target to be achieved by 2010

	2006		2010 targets[1]	
	Quantity	Ratio per 100,000 population	Quantity	Ratio per 100,000 population
General practitioners	44.564	19.9	70,782	30
Specialist	12.374	5.5	21,234	9
Dentists	11.289	5.1	25,953	11
Nurse	308.396	137.9	372,308	158
Midwife	79.152	35.4	176,954	75
Pharmacist	10,207	4.6	21,234	9

Notes: The targets set by the MoH were to be achieved by 2010 (NIHRD, 2007)

Even if they have the recommended number of GPs, health centres in Indonesia suffer from a high rate of absenteeism. A study by Chaudhury et al. (2006) shows that the absenteeism rate of doctors in health centres in Indonesia is 40%. That is, GPs spend 40% of their time allocated to providing medical care services in conducting other business. This rate is much higher than for other countries, including Bangladesh, Peru and Uganda. This high rate of absenteeism indicates that much time is spent on administrative matters. It is a common practice that a GP in a health centre is also appointed the head of the health centre, which unavoidably requires much time and energy to be spent for administrative tasks.

If all GPs either working in public facilities or opening a private practice or both are considered, there is a significant discrepancy between rural and urban areas. Table 3.5 shows that both measured in number and in ratio per 100,000 population, the rural regions are far behind urban areas in their numbers of GPs, even on Java and Bali. The distribution of midwives, on the other hand, is higher in rural than in urban areas.

Table 3.5 The distribution of general practitioners and midwives among regions in Indonesia, 2006

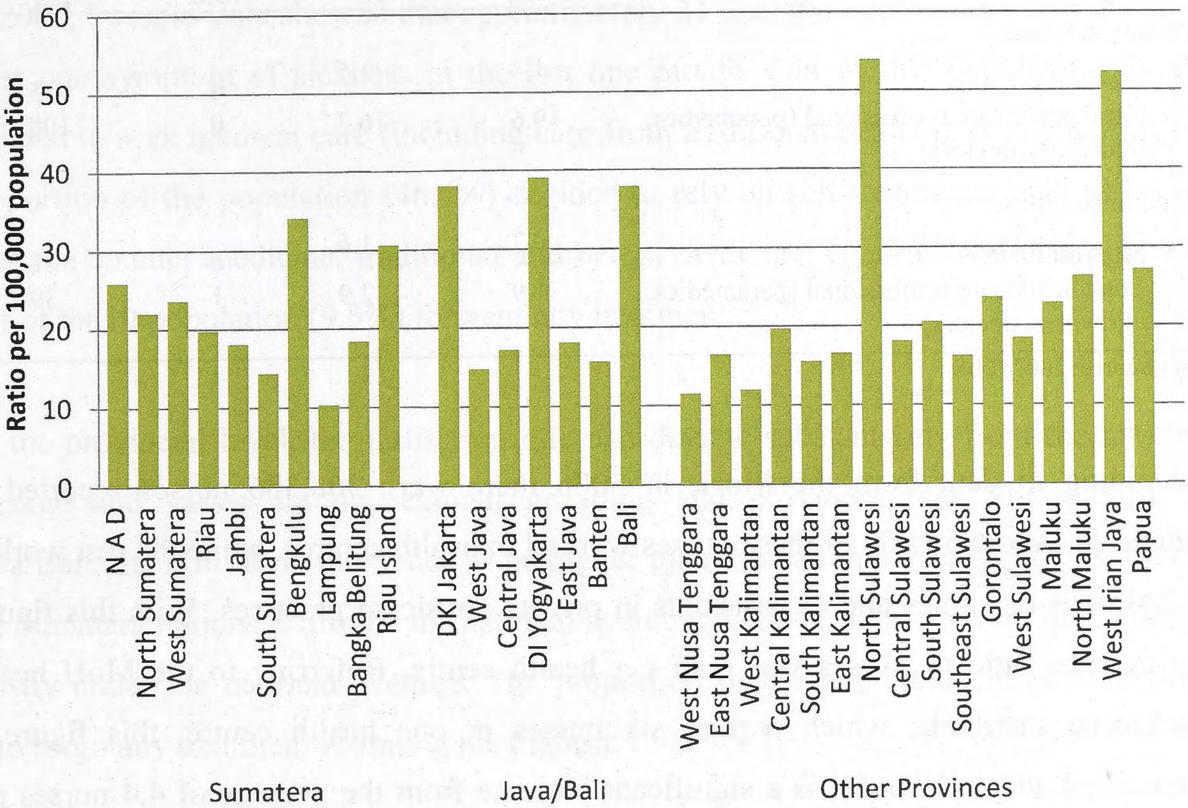
	General practitioners		Midwives	
	Number	Ratio per 100,000 population	Number	Ratio per 100,000 population
Java/Bali	23,944	18.5	33,755	26.1
Urban	20,896	34.1	15,388	25.1
Rural	3,048	4.5	18,367	27.1
Outside Java/Bali	15,740	18.1	45,906	52.8
Urban	11,187	40.9	12,421	45.4
Rural	3,141	8.3	20,957	55.1

Date source: PODES 2006

Another variation of medical doctor (GPs and specialists) distribution can be observed among provinces (see Figure 3.4). This variation was not specific to provinces in or outside of Java/Bali, but also revealed itself within regions. However, this variation should be observed cautiously, as it does not take into account the area of coverage; that is, high ratio does not mean easy access. Taking Yogyakarta and West Papua as examples, the ratio of medical doctors in these provinces is relatively high, but due to different reasons. In Yogyakarta, the high ratio of medical doctors means better access, as the population is confined in a relatively small geographic area and access to modern transportation is easy. West Papua, on the other hand, is a very large province and its small population is spread out over a vast area. For this reason, transportation access to medical doctors is quite difficult. Therefore, in West Papua, the high doctor to population ratio does not guarantee easy access to health workers.

The distribution of midwives is more equitable compared to medical doctors. In fact, there are more midwives in rural areas than in urban areas. A high ratio of midwives per population in rural areas can mainly be attributed to the 1990s government program to assign a midwife to every village (such health professionals are thus called 'the village midwife').

Figure 3.5 The number of medical doctors per 100,000 populations by province, Indonesia 2007



Data source: calculated from MoH data and population projection

In 2006 in Java/Bali, there were about 12 midwives per 1,000 births. Outside Java/Bali, however, the number of midwives was 22 per 1,000 births (Rokx et al., 2010). At this level, a midwife on average delivers one birth per week. While this figure shows that access to midwives in rural areas is better, it also reflects the low demand for midwives, especially in Java/Bali owing to these regions having more options for choice of health professional, such as GPs and obstetric gynaecologists. The low demand for midwives in one of the reasons behind the decreasing number of village midwives in the 2000s.

The quantity of health professionals in each type of health facility also varies between public (public hospitals, health centres and their auxiliary health centres) and private facilities (private hospitals, clinics and private practices). On average, public facilities have more health professionals than do private facilities (see Table 3.6). However, the variation among individual health facilities is also high.

Table 3.6 Number of health professionals per health facility, Indonesia 2007

	Average quantity per health facility			
	Mean	SD	Min	Max
Public facilities				
Medical doctors	1.4	1.5	0	15
Total healthcare professional (paramedics, midwives, doctors)	19.6	16.3	0	108
Private facilities				
Medical doctors	0.7	1.6	0	19
Total healthcare professional (paramedics, midwives, doctors)	1.9	2.9	1	39

Data Source: 2007 IFLS

According to data from the MoH, in 2006 there were 308,306 nurses reported in Indonesia. About 55,000 of these nurses worked in health centres, while the rest worked in hospitals or clinics and as assistants in private physician practices. With this figure, the average ratio of nurses was 6.46 per health centre. Referring to the MoH health workforce standards, which require six nurses in one health centre, this figure is considered adequate and it is a significant increase from the average of 4.4 nurses per health centre in 2004. This rapid increase in the nurse to population ratio is the result of increased nurse production. It is estimated that 34,000 newly trained nurses enter the labour market every year (Rokx et al., 2010).

B. Healthcare Utilisation

The improvement of the accessibility, affordability and quality of healthcare providers is expected to induce healthcare utilisation. In the end, however, it is the people who eventually decide whether to seek care and which provider to choose. Therefore, it is equally important to explore the demand for healthcare by the characteristics of the users.

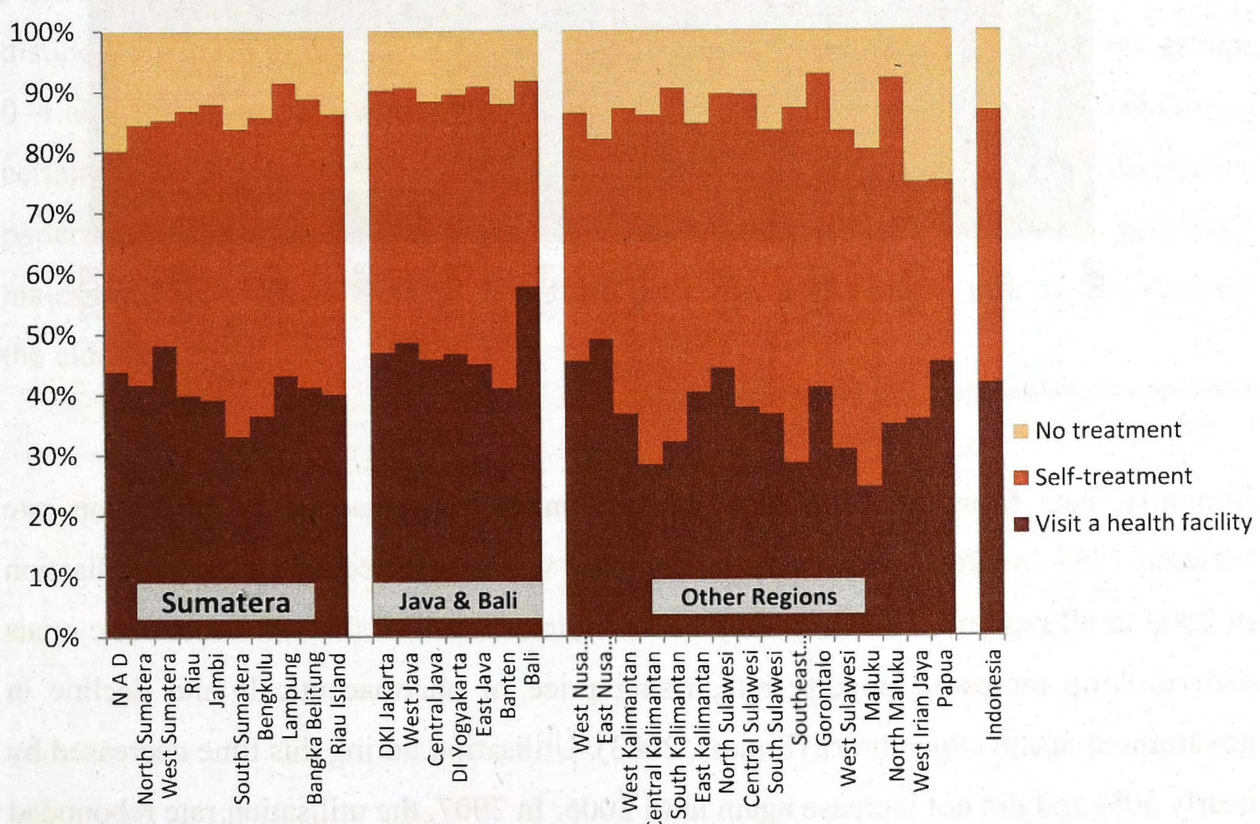
This section briefly explores the magnitude and trend of healthcare utilisation in Indonesia, with a focus on the variability of utilisation by demographic characteristics and regional differences. In doing so, healthcare utilisation will be represented by the utilisation rate and choice of provider.

B.1. Utilisation Rate

In 2007, Susenas data showed that approximately 31% of the population experienced at least one symptom of sickness in the last one month. Out of this population, 44.1% decided to seek medical care (including care from traditional healers). A slightly higher proportion of the population (46.4%) decided to rely on self-treatment, such as taking over the counter medicine, traditional and herbal medicine, coining[8] and massage. The rest of the ill population (9.5%) forwent any treatment.

At the provincial level, the utilisation rate can deviate substantively from the national average and varies among regional grouping and provinces (see Figure 3.6). In Java/Bali, the utilisation rate tends to be higher than the national average. Utilisation in the Sumatera regions is around the national average; while in other regions, utilisation is mostly under the national average. The proportion of the population in other regions who forgo any treatment is among the highest.

Figure 3.6 Healthcare-seeking behaviour among the ill population, Indonesia 2007

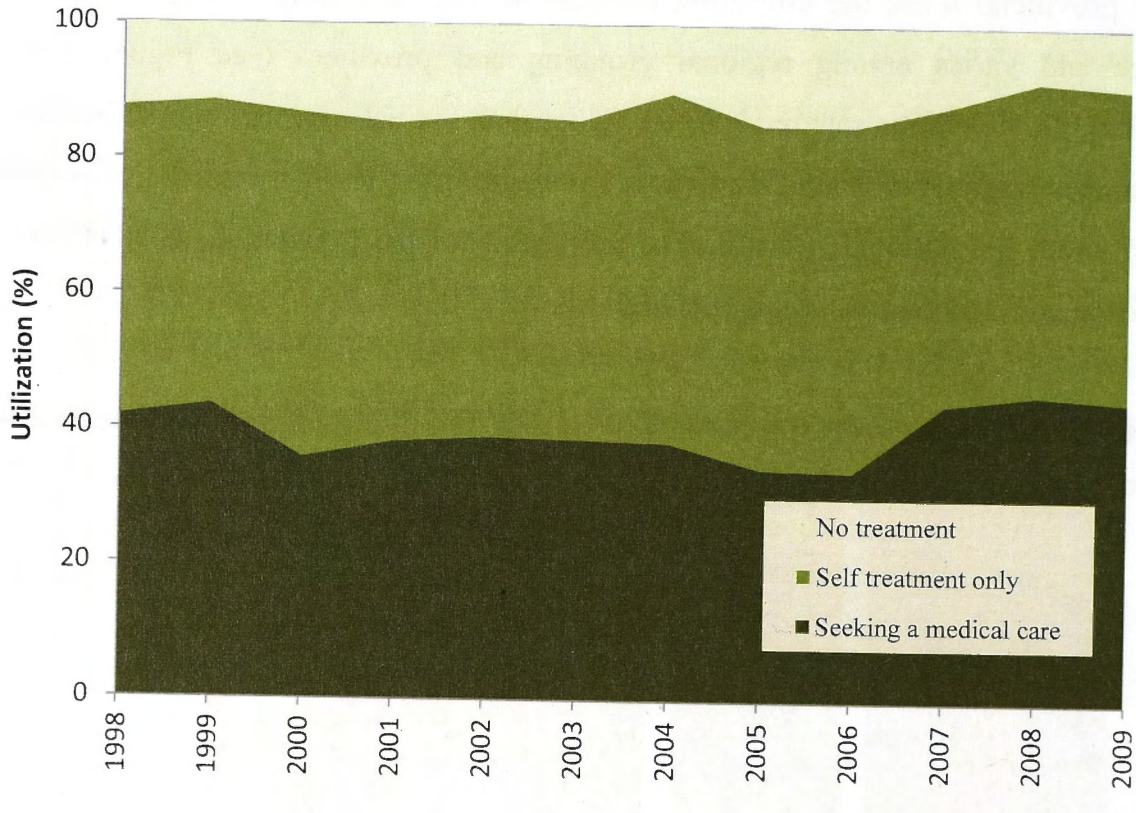


Data source: calculated from 2007 Susenas

8 'Coining' (*kerokan* is the local term) is the practice of rubbing the back and neck of an ailing person with the edge of a coin to bring up red welts. It is widely practised in Indonesia and has been thought an effective cure for *masuk angin* (the Indonesian equivalent of catching a cold).

Looking at the trends over time, the utilisation rate has increased slightly in the last decade from 41.9% in 1998 to 44.7% in 2009[9] (see Figure 3.7). During this period, however, there have been significant fluctuations, with a drop in utilisation in 2000 to 35.8%, remaining generally constant at around 2000's level until 2006. In 2007, there was a marked increase in utilisation to 44.1%.

Figure 3.7 Utilisation of healthcare services among the ill population, Indonesia 1998–2009



Data Source: Calculated from 1998–2009 Susenas

Similarly, data from the IFLS also shows a modest increase in the utilisation rate between 1997 and 2007. However, this increase was interjected by a drop in utilisation in 2000 in all regions. This drop may be an indirect result of the 1998 economic crisis and resulting increased poverty rate, rising price of pharmaceuticals and decline in government health expenditure (Simms, 2003). Utilisation during this time decreased by nearly 60% and did not increase again until 2006. In 2007, the utilisation rate rebounded and even surpassed the 1997 rate, especially in Sumatera, Java and Bali (see Table 3.7).

---

[9] 1998 Susenas was the earliest round of the Indonesia National Social and Economic Survey (Susenas) with which subsequent data on healthcare utilisation is comparable.

Table 3.7 Healthcare utilisation and self-treatment

	Outpatient utilisation (%)			Self-medication: OTC medicine (%)		
	1997	2000	2007	1997	2000	2007
All sample	19.1	14.6	21.1	59.9	31.8	59.8
Sumatera	15.5	14.7	19.0	57.0	31.2	58.1
Java and Bali	20.4	14.9	22.4	60.8	33.6	58.9
Other provinces	18.5	13.6	17.8	60.0	27.3	58.6

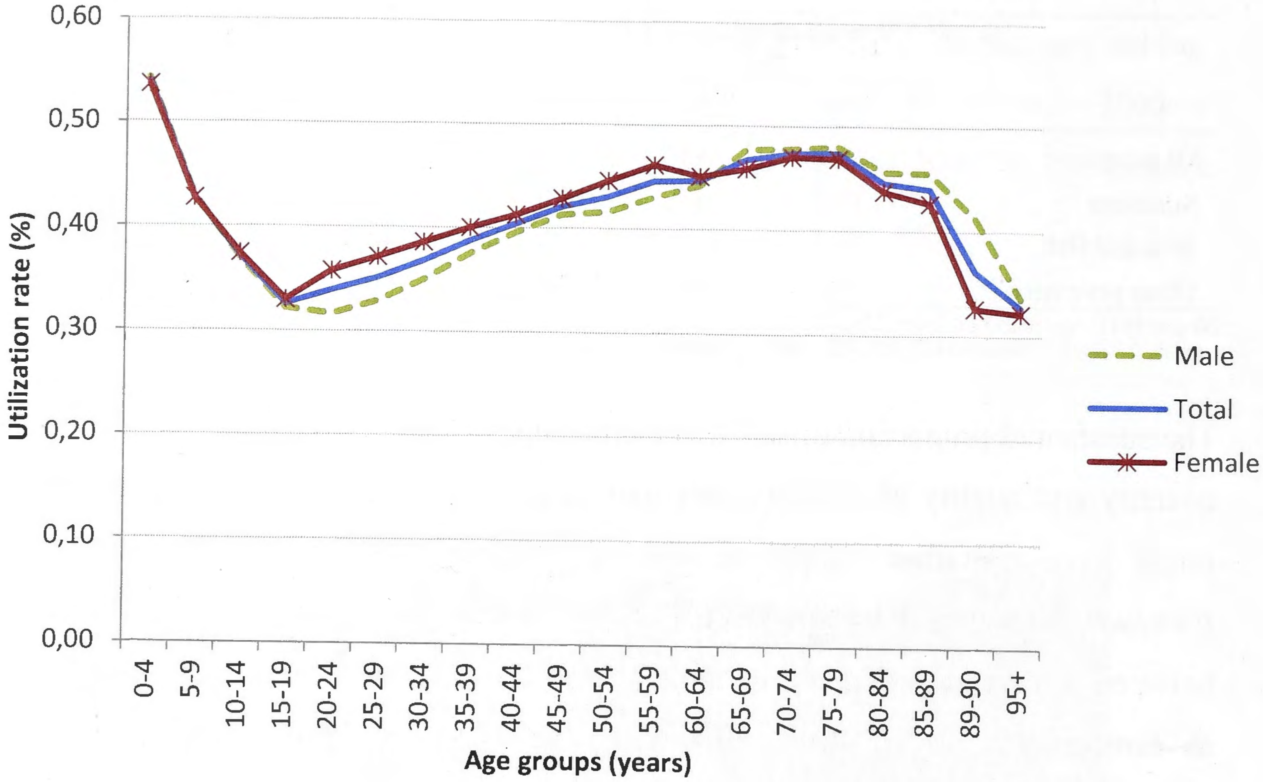
Notes: OTC=over-the-counter. Data Source: 2007 IFLS. Taken and modified from Rokx et al. (2010).

The substantial proportion of self-treatment suggests that despite major improvement in quantity and quality of infrastructure and health workforce, factors other than supply might have restrained people in seeking medical care. The healthcare utilisation framework developed by Andersen (1995) can help in investigating the associations between healthcare utilisation patterns and various factors influencing utilisation such as demographic, social structure, health beliefs, personal and family resources and perceived and evaluated need of healthcare.

Figure 3.8 shows the healthcare utilisation rate by all age groups in 2007.[10] There is a distinctive pattern of utilisation across different stages of life. First, between age groups 0–4 and 15–19, utilisation begins relatively high, decreasing with age until reaching a certain point (16 years for females and 18 years for males). The second distinctive pattern is the increase in visits from age 17 among females and 19 years of age among males until around age 70 to 74. The third pattern is a decreasing rate of visits among the elderly.

[10] A similar pattern was found for visit rates across various time frames from 1996 to 2009 Susenas, but with a shift (not tilt) in overall utilisation for all age groups of a similar degree. This shift in utilisation indicates the involvement of exogenous factors, such as income shock or public financing, affecting utilisation in all population groups, regardless of age.

Figure 3.8 Utilisation rate of any health facility by age group among the ill population, Indonesia 2007



Data source: Calculated from 2007 Susenas

This trajectory is roughly similar to previous studies in other countries such as in the US (Andersen and Aday, 1978) and in Italy (Wolinsky, 1978), where the extreme age groups (that is, children and the elderly) were found to use more services than other age groups. A cohort analysis of the use of health services by elderly Americans by Wolinsky et al. (1986) revealed an inverse J-curve relationship with age among adults and the elderly, with a turning point at about age 80. A similar trend can be observed in Indonesia from cross-sectional data (Susenas), but with an earlier turning point at about age 70 to 74 years (see Figure 3.8).

The effect of age on healthcare utilisation, although significant, is relatively small, according to some studies (Andersen and Aday, 1978, Bellon Saameno et al., 1995, Wolinsky, 1978). However, the use of a monotonic trend of healthcare utilisation can underestimate the effects of age due to fluctuations in utilisation across age. Looking at the distinctive patterns for each stage of life—that is, children, adults and the elderly, as shown in Figure 3.8—the effects would probably be higher if each of these stages were analysed separately. This issue will be dealt with in more depth in Chapter 4.

Figure 3.8 above also indicates a difference in utilisation rate between male and female. In the early ages until around age 16, the utilisation rate of males and females is relatively similar. Beginning at age 17, females use health services more than do males, until reaching a turning point at age 70–74. After that, the visit rate among males is higher than for female.

A higher utilisation rate among females during adulthood may be related to maternal-related health at reproductive age, as has been shown elsewhere by Beland (1988). However, using 2007 IFLS data and controlling for prenatal-related purposes, the visit rate among females was still higher than for males. This is consistent with previous studies in other countries, which generally show higher use of services among females, even after adjusting for health needs (Mendoza-Sassi and Béria, 2001).

B.2. Choice of Providers

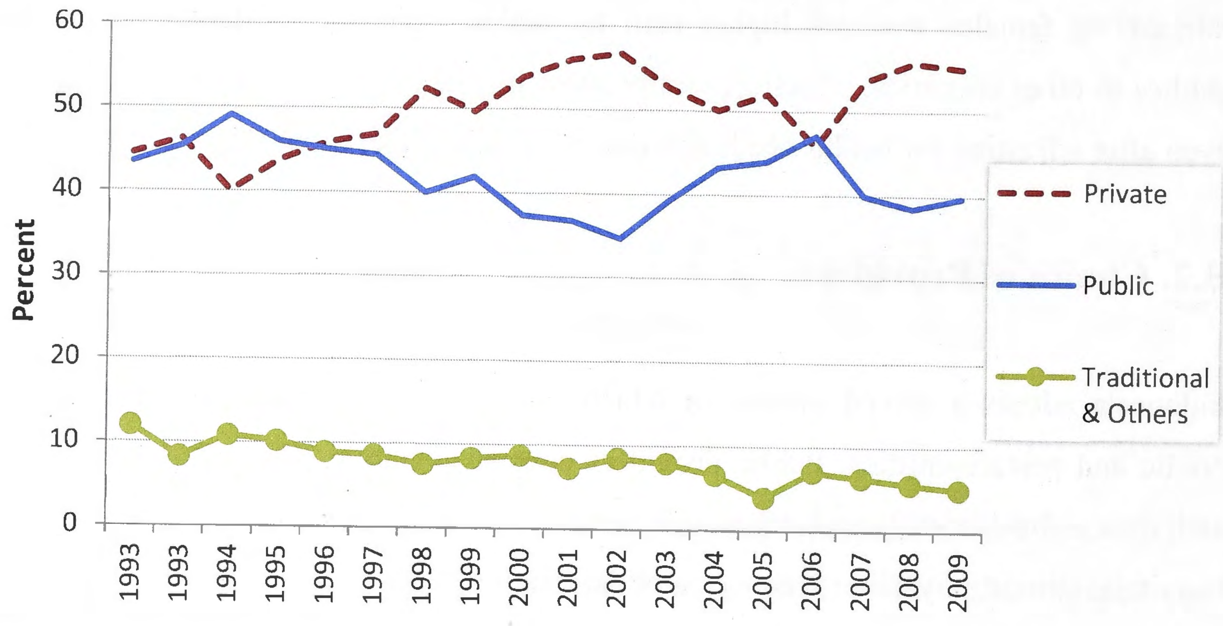
Indonesia adopts a mixed system in which healthcare delivery is provided by both public and private entities. Public providers consist of public hospitals, health centres and their subsidiaries (auxiliary health centre).[11] Private providers consist of private hospitals, clinics, physician practices and paramedics, midwives and nurses. Traditional providers, such as *dukun* (traditional healer) and traditional midwives are also private. However, as they are not formal healthcare providers as recognised by the MoH, in this study, traditional providers are treated as a separate entity.

The administrative coverage of public providers on most occasions is parallel to the regional political level and boundaries. For example, an auxiliary health centre serves a specific village, a health centre serves a sub-district and a hospital provides services at the district and provincial levels. In contrast, private healthcare and traditional practices have a more diverse coverage and are less restricted by political boundaries.

[11] Auxiliary health centres are operated at the village level, while health centres are operated at sub-district level. Administratively, auxiliary health centres are an extension of health centres, but with much less technological capability and with their medical personnel assigned by the health centres. In this study, the term 'health centre' refers to both health centres and auxiliary health centres.

In the primary healthcare initiative of early 1970, the role of the public sector was preeminent. Nowadays, the private sector has grown extensively, and in some cases has surpassed public healthcare provisions. Between 1994 and 2002, the share of public healthcare in the utilisation rate decreased by 14.3 percentage points. In 2006, however, it bounced back closer to its 1994 level, before decreasing again in 2007 (see Figure 3.9). The utilisation of private providers also fluctuates, but it has consistently surpassed utilisation of public providers since 1996.

Figure 3.9 Share of utilisation based on health provider type, Indonesia 1992–2009



Data source: 1992–2009 Susenas

Utilisation of private providers fluctuates and seems to move in the opposite direction to utilisation of public providers. This is contributed by a substitution effect between private and public providers. A study by Pradhan (2007) indicated that as a result of the Social Safety Net (SSN) health card program financial crisis, in 1999 a substitution from private to public healthcare providers occurred among non-poor health card owners. In 2005, the government rolled out health insurance for the poor (Askeskin) and possibly continuing, but incomplete, the substitution effects from private to public providers (World Bank, 2008). The largest increase of utilization of public providers resulted from the increase of public service supply (Pradhan, 2007).

Under the Askeskin scheme, a household identified as poor is eligible for an Askeskin card for all its members. With an Askeskin card in hand, a person can seek outpatient and inpatient care free of charge or at a significantly reduced price, depending on the type of treatment sought. As initially, the Askeskin card was valid only at public providers, this program potentially drove Askeskin cardholders to switch from private to public providers for their medical care. However, studies by World Bank (2008) and Sparrow (2010) do not find evidence of substitution effects from private to public healthcare providers. Moreover, since 2010, private providers have been included as preferred providers of Askeskin as well, so that people do not have to switch to private providers to enjoy the discounted service.

In 2007, 16.3% of the ill population visited health centres, making health centres the most visited provider, followed by, in descending order, paramedic, nurse and midwife practices, GPs and clinics, public hospitals, private hospitals and other facilities, such as *Posyandu* or village maternity posts and traditional practices. Table 3.8 shows visit rates[12] to various healthcare providers in Indonesia.

Table 3.8 Visit rates to healthcare providers, Indonesia 2007

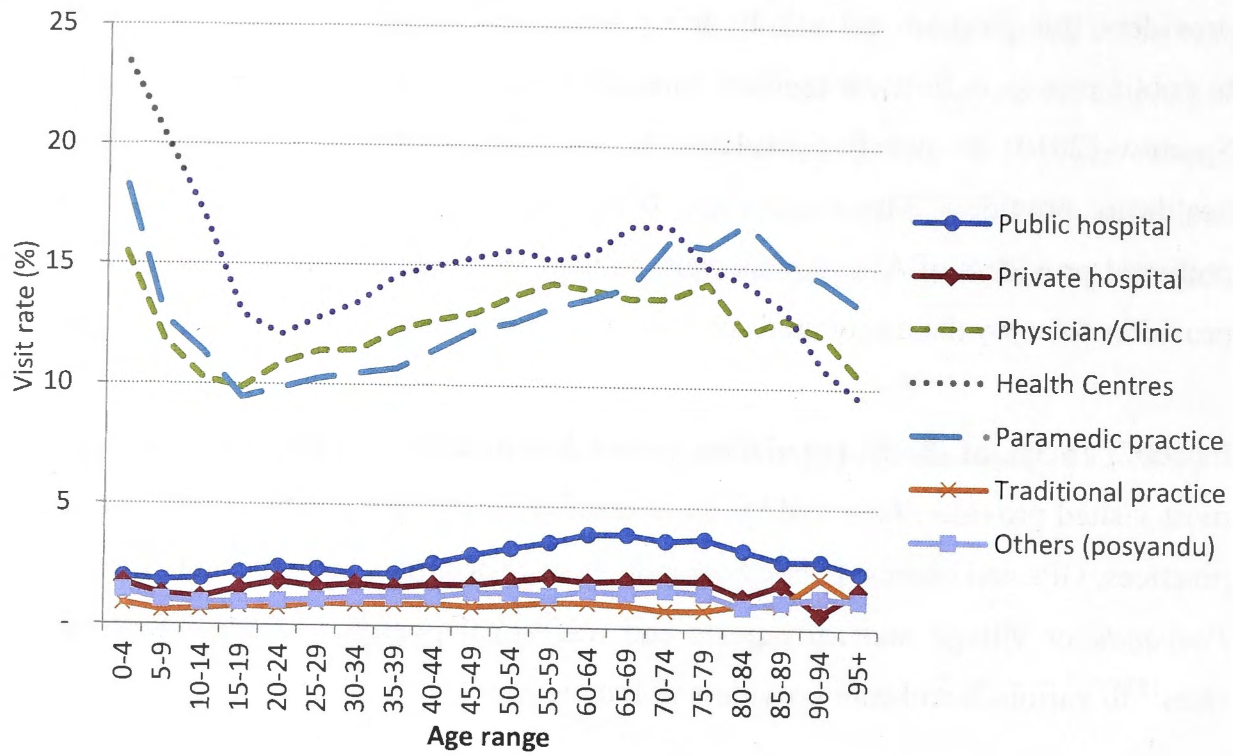
Healthcare providers	Utilisation rate (%)		
	Male	**Female**	**Total**
Public hospital	2.62	2.54	2.58
Private hospital	1.69	1.66	1.68
Physician/Clinic	13.01	12.30	12.65
Health centres	15.46	17.04	16.25
Paramedic/nurse/midwife	12.40	13.03	12.72
Traditional practice	0.86	0.84	0.85
Others (*Posyandu*)	1.24	1.23	1.24

Source data: 2007 Susenas

The previous section described a distinct pattern of utilisation rates among children, adults and the elderly. Decomposition of the utilisation rate into type of healthcare provider by age group shows that the trajectories of visits to health centres, GPs/clinics and paramedics (and visits to private hospital practices to some extent) are quite similar across the groups. Rates are high then decrease for children, increase by age for adults and decline in later years (see Figure 3.10). The effect of age on the utilisation rates of private, traditional practices and *Posyandu* seems marginal.

12 'Visit rate' is the percentage of the ill population that visited a provider at least once in the previous month. A person can visit several providers in a month. In this study, visit rate is different from utilisation rate, which measures the percentage that visited health facilities.

Figure 3.10 Visit rate to healthcare provider by age group, Indonesia 2007

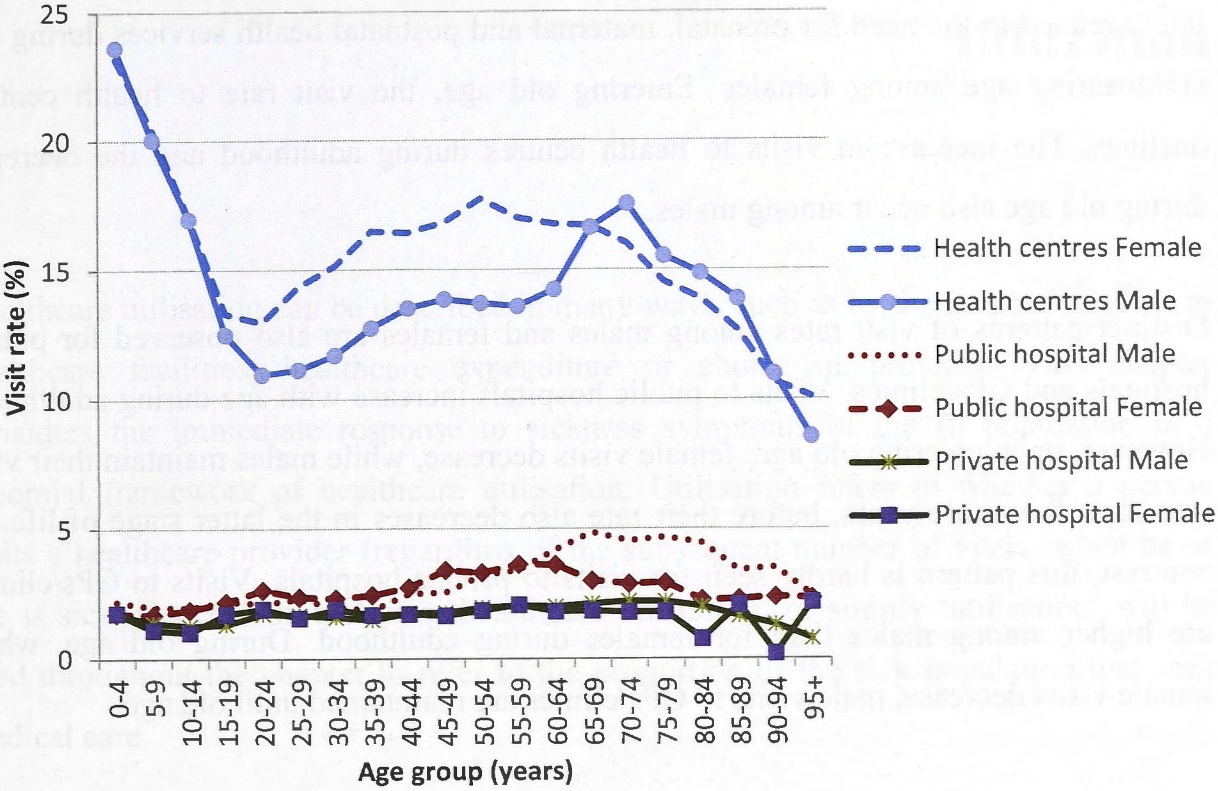


Source: calculated from 2007 Susenas

The high utilisation rate among children might be related to the fact that the health system has positioned health centres, midwives and GPs as the main delivery points for maternal and child health, which subsequently drives parents or caregivers to go to these facilities. The increase of visits to public hospitals during adulthood is probably related to the fact that, at this stage of life, non-communicable diseases are more prevalent and thus people choose facilities with high medical capability and sophisticated technology.

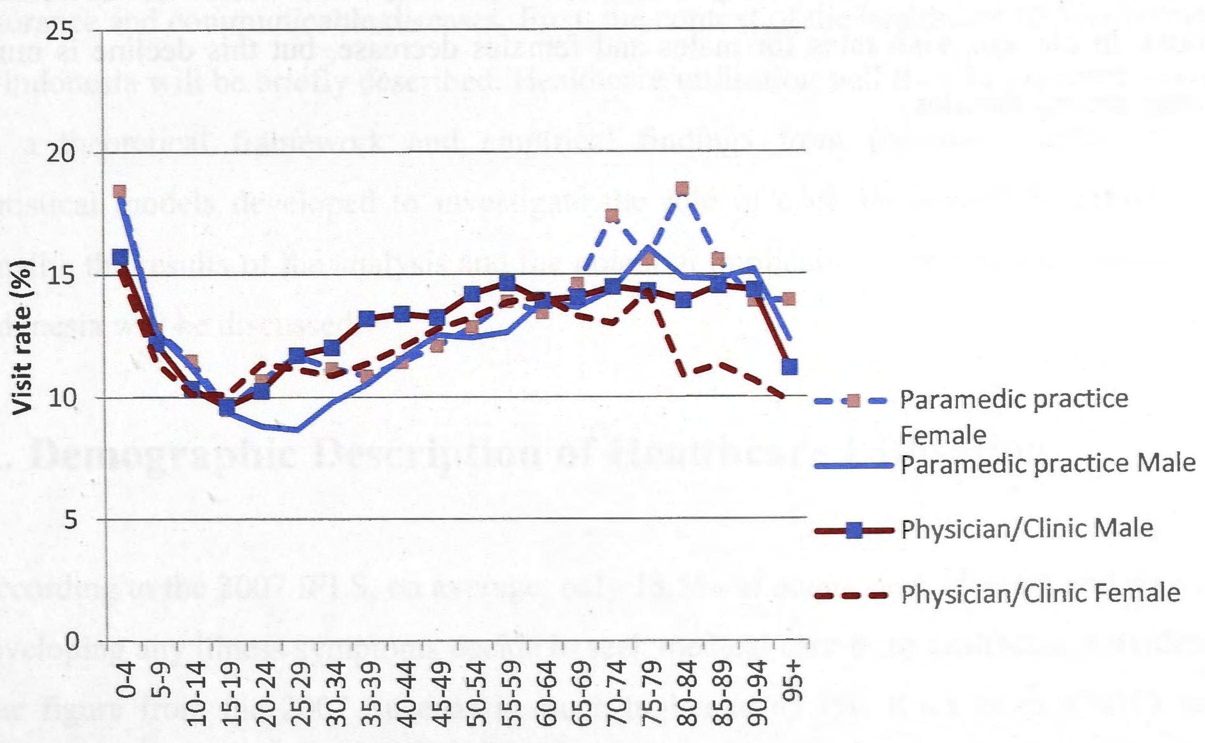
As described previously, the average visit rate for each type of healthcare provider shows little effect of sex. However, aggregated utilisation conceals variations based on age and sex to certain types of healthcare provider. Further disaggregation of utilisation by age and sex reveals variations in utilisation for health centres, public hospitals, paramedics and GPs/clinics (see Figure 3.11). A little variation is observed in the visit rate to traditional and other types of provider, but this is not discussed here.

Figure 3.11 The visit rate to health centres and public and private hospitals among males and females by age group, Indonesia 2007



Data Source: calculated from 2007 Susenas

Figure 3.12 The visit rate to paramedic practices and GPs/clinics among males and females by age group, Indonesia 2007



Data Source: Calculated from 2007 Susenas

During adulthood (starting from about age 15), the visit rate to health centre increases with age until around age 50. The rate for females is higher than for males. This is most likely related to the need for prenatal, maternal and postnatal health services during the childbearing age among females. Entering old age, the visit rate to health centres declines. The increase in visits to health centres during adulthood and the decrease during old age also occur among males.

Distinct patterns of visit rates among males and females are also observed for public hospitals and GPs/clinics. Visits to public hospitals increase with age during adulthood. However, upon entering old age, female visits decrease, while males maintain their visit rate for a few more years, before their rate also decreases in the latter stage of life. In contrast, this pattern is hardly seen for visits to private hospitals. Visits to GPs/clinics are higher among males than for females during adulthood. During old age, while female visits decrease, male visits to GPs/clinics are maintained until old age.

Overall, the pattern of utilisation and visits among males and females can be differentiated according to the stages of life; that is, childhood, adulthood and old age. During childhood, the visit rate among males and females is similar. During adulthood, females visit health centres at a higher rate than do males, while males visit GPs/clinics more. In old age, visit rates for males and females decrease, but this decline is much faster among females.

Chapter 4
Determinants of Healthcare Utilisation

Healthcare utilisation can be described in many ways, such as by the number of visits to healthcare facilities, healthcare expenditure or choice of provider. This chapter considers the immediate response to sickness symptoms of the ill population in a binomial framework of healthcare utilisation. Utilisation refers to whether a person visits a healthcare provider (regardless of the subsequent number of visits) when he or she is sick. Henceforth, the term 'healthcare utilisation' or simply 'utilisation' will be used throughout the chapter to refer to the proportion of the sick population that seek medical care.

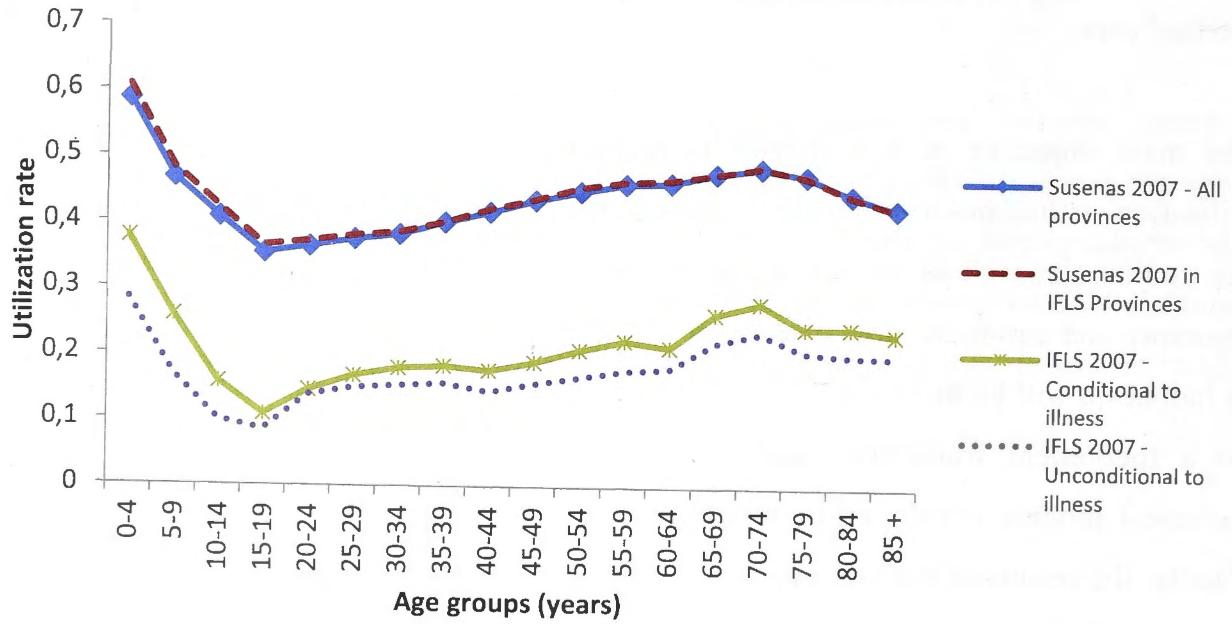
The main objective of this chapter is to investigate the determinants of healthcare utilisation in Indonesia, with particular interest on basic demographic factors such as age and sex, as well as on non-demographic factors such as income, education, health insurance and communicable diseases. First, the context of the healthcare utilisation rate in Indonesia will be briefly described. Healthcare utilisation will then be explored based on a theoretical framework and empirical findings from previous studies. Next, statistical models developed to investigate the role of each factor will be presented. Finally, the results of the analysis and the potential implications for future utilisation in Indonesia will be discussed.

A. Demographic Description of Healthcare Utilisation

According to the 2007 IFLS, on average, only 18.5% of adults (age 15 years and above) developing any illness symptoms decide to seek medical care from healthcare providers. The figure from the 2007 Susenas is much higher at 41.7%. Rokx et al. (2010) has argued that the difference in the utilisation rate reported in the Susenas and IFLS data is the result of the limited coverage of IFLS, which is representative of only 18 provinces, compared to Susenas, which covers all 33 provinces (Rokx et al., 2010). Consequently, the utilisation of healthcare in provinces not included in the 2007 IFLS might have increased the utilisation average, had they been included in the survey.

However, upon further investigation, this may not be the case. Figure 4.1, referring to Susenas data, shows that healthcare utilisation in all provinces is not different from the utilisation in IFLS-area provinces. Further, the utilisation rate in the provinces in which both Susenas and IFLS are conducted is similar. In other words, the difference in the utilisation rate recorded by Susenas and recorded by IFLS may not be due to the difference in the coverage of the surveys. Moreover, since IFLS based their sampling methodology and areas on 2007 Susenas, it is unlikely that 2007 IFLS samples represent different populations from Susenas.

Figure 4.1 The healthcare utilisation recorded in 2007 IFLS and 2007 Susenas, by age groups



The differences in the utilisation rate may come from the instruments used to collect the data; and specifically, in the identification of sickness among respondents (the denominator part of the calculation of utilisation). In IFLS, sickness is identified as 'whatever symptoms' a respondent had during the four weeks prior to the interview. The questionnaire listed 18 symptoms for the respondents to choose from (yes or no option). Susenas, on the other hand, provides a list of 'health complaints' experienced in the last one month prior to the interview, comprising only eight types of complaint[13],

[13] The sickness symptoms listed in 2007 IFLS are headache, runny nose, cough (three types), difficulty breathing (two types), fever, stomach ache, nausea/vomiting, diarrhoea (three types),

which are also included in the 18 complaints listed in IFLS. The fewer symptoms listed could cause respondents in the Susenas to be less likely to identify as sick (31.59%) as compared to the IFLS (74.6%). Meanwhile, the eight conditions listed in both Susenas and IFLS are more serious than the other 10 conditions, so that they are more likely to drive people to seek help. This is highly likely to be the reason for the difference. Unfortunately, this argument cannot be verified by comparing utilisation among the general population (that is, unconditional of sickness symptoms), since Susenas only records conditional utilisation.

Despite the difference in the magnitude of utilisation, the patterns of utilisation across age groups from 2007 Susenas and 2007 IFLS are similar, showing three distinctive utilisation trajectories during the lifetime of respondents;[14] that is, decreasing during childhood (0–14 years), increasing during adulthood (15–69 years) and decreasing again during old age (70 years and above).

The analysis in this chapter will be based primarily on data from 2007 IFLS. IFLS captures more variables related to the healthcare utilisation determinants. Further, 2007 IFLS provides facility-based data, such as the cost and the quality of services, as well as the financial and geographical accessibility. Facility-based data can be matched with individual and household data to provide a complete set of demographic, social economic, health need and provider characteristics. These two conditions—availability of facility data and the link to household data—are the key for analysing the roles of provider characteristics and their interaction with users, as will be dealt with in more detail in Chapters 6 and 9. Previous studies in other countries recognise this pattern and have developed separate models for children and adults (including the elderly) (Borah, 2006, Halldórsson et al., 2002, Minkovitz et al., 2002, Riley et al., 1993, Palacio-Vieira et al., 2012).

---

swollen legs, skin infection, eye infection, toothache and cold sores. The list of health complaints in 2007 Susenas includes fever, cough, flu/cold, asthma/breathing difficulty, diarrhoea, headache, toothache and others.

[14] Since this is a cross-sectional setting, the distinctive pattern across ages does not necessarily reflect the pattern along age in birth cohort setting. So far, there is no study using longitudinal data to portray the cohort trend of utilisation in Indonesia. A longitudinal study by Wolinsky et al. (1986) in the US shows a similar trend in utilisation by cohorts.

Previous studies have also found differences in utilisation among children, indicating that factors influencing utilisation are specific to children. During childhood, parents or carers have been widely recognised as influential in decisions regarding children's interactions with healthcare providers (Cafferata and Kasper, 1985, Carpenter, 1980, Minkovitz et al., 2002).

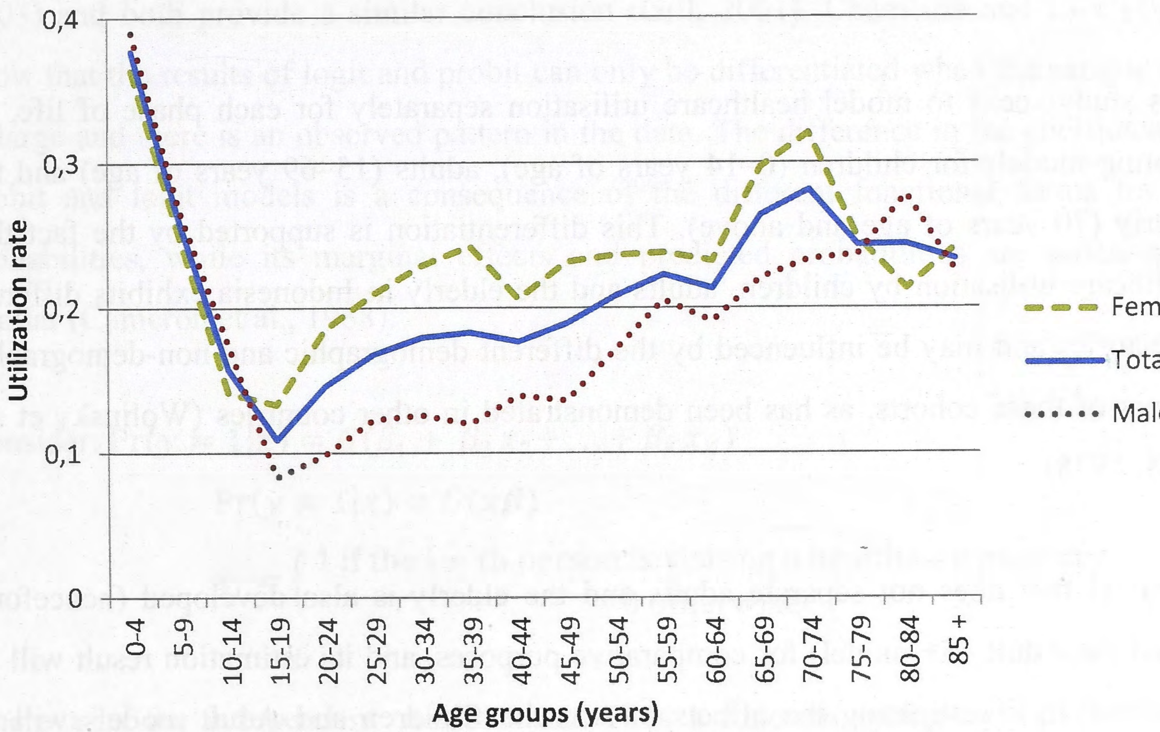
These associations show the need to consider parents or carers' characteristics in understanding the pattern of health utilisation among children. The influence of parent's behaviour and their psychosocial and economic status are often quite significant, especially for younger age children, when the decision to visit healthcare providers is mainly made by parents or carers (Janicke et al., 2001). Some of the parents or carers' characteristics associated with healthcare utilisation among children include self-reported health status and poverty level (Minkovitz et al., 2002), mother's retrospective healthcare use and maternal psychosocial status (Janicke et al., 2001), and mother's employment and ethnicity, health status, education and family affluence (Palacio-Vieira et al., 2012, Newacheck and Halfon, 1986, Horwitz et al., 1985, Wolfe, 1980).

Although many studies do not distinguish the elderly from adults and thus assume monotonic correlation of age and utilisation (Jatrana and Crampton, 2010, Qian et al., 2009, Canaviri, 2007, Habtom and Ruys, 2007, Borah, 2006, Sahn et al., 2003), other studies have found differences in the pattern of healthcare utilisation between these cohorts. Recognising this unique pattern of elderly healthcare behaviour, separate models were developed for the elderly (Suominen-Taipale et al., 2006, Foreman et al., 1998, Wolinsky et al., 1986, Wolinsky et al., 1988).

For studies on healthcare utilization using the Indonesian setting, existing studies (Rokx et al., 2010, Hidayat and Pokhrel, 2009, Hidayat et al., 2004, Chernichovsky and Meesook, 1986) have not developed different models for adults and the elderly. This is despite the pattern of healthcare utilisation in Indonesia showing a different trajectory by age between adults (age 15–69) and the elderly (age 70 and above).

Both 2007 Susenas and 2007 IFLS show that the utilisation rate among elderly males and females starts to decline at age 70. The declining rate of physician visits among the elderly in the US was studied by Wolinsky et al. (1988), who found this decline was due to an accelerated decreased response to health limitations in activity. Other possible explanations include the substitution of physician visits with other institutions or informal services by this age group, including treatment by family members, sons and daughters (Byrne et al., 2009, Horowitz, 1985); an increased likelihood that the elderly will have lost their long-standing personal physicians; either a physician or patient belief that medical care is no longer beneficial; or simply a decline in the cohort that traditionally demonstrated high utilisation.

Figure 4.2 Healthcare utilisation patterns across age by sex, Indonesia 2007



Source: calculated from 2007 IFLS

When considering the potential role of sex in healthcare utilisation at each stage of life, it is generally found that both males and females have similar patterns of decreasing utilisation in childhood, increasing during adulthood and again decreasing in old age. The utilisation rate during childhood seems to be similar for males and females. During adulthood, utilisation among females is higher than among males, until reaching a certain age (approximately 70–74 years). Beyond age 70, the difference in the utilisation between males and females is not conclusive (see Figure 4.2), even though males seem to exceed females in utilisation rate. Referring to 2007 Susenas (see Figure 3.8), the utilisation rate of healthcare among elderly males is higher compared to among elderly females.

B. Model Development

B.1. Specification

The analysis is conducted using data from the 2007 wave of the IFLS. The IFLS is a longitudinal survey conducted in several waves; that is, 1993, 1997, 2000 and 2007. It was conducted in 18 provinces[15] (out of 33 provinces in Indonesia) and the sample size represents 83% of the Indonesian population (Strauss et al., 2009). Only data from the 2007 wave of the IFLS is used in the statistical model in this chapter, so it is cross-sectional data.

This study seeks to model healthcare utilisation separately for each phase of life, by creating models for children (0–14 years of age), adults (15–69 years of age) and the elderly (70 years of age and above). This differentiation is supported by the fact that healthcare utilisation by children, adults and the elderly in Indonesia exhibits different trajectories and may be influenced by the different demographic and non-demographic factors of these cohorts, as has been demonstrated in other countries (Wolinsky et al., 1988, 1978).

A model that does not separate adults and the elderly is also developed (henceforth called the Adult 15+ model) for comparative purposes, and its estimation result will be provided. In investigating the effects of sex, the Children and Adult models will be modified further by running the model for males and females separately. Further modification includes modifying the data setting for independent variables, such as running the model for dummy household income level (category) and its continuous form.

Binary outcome models will be used in this determinant analysis. This is a simplified form of choice model that assumes that people face two mutually exclusive options when they are sick: to seek care by visiting a healthcare provider, or not to seek care. Within the binary outcomes model, the logit or probit model is used widely in the study of healthcare demand (Ensor and Cooper, 2004, Sahn et al., 2003, Lance, 2003). In this

[15] Provinces covered in 2007 IFLS include DI Aceh, North Sumatera, West Sumatera, South Sumatera, Lampung, DKI Jakarta, West Java, Central Java, DI Yogyakarta, East Java, Bali, West Nusa Tenggara, South Kalimantan and South Sulawesi.

study, the logit model is preferred for its simplicity in the interpretation, by taking advantage of its odds ratio evaluation. In addition, bivariate probit is used in the diagnosis of endogeneity. Despite its simplicity, the binary choice model is widely used for its advantages in helping to understand the basic idea of healthcare-seeking behaviour. The nature of choice makes it easy to communicate to a wider audience, such as policy makers.

Conventionally, the choice between logit and probit has been a matter of taste (Hahn and Soyer, 2005). The choice does not make any great difference (Greene and Zhang, 2003) and both provide a similar conclusion (Gill, 2001). Chambers and Cox (1967) show that the results of logit and probit can only be differentiated when the sample size is large and there is an observed pattern in the data. The difference in the coefficient of probit and logit models is a consequence of the different functional forms for the probabilities, while its marginal effects and predicted probabilities are much more similar (Cameron et al., 1988).

Consider: $\Pr(y=1|x) = G(\beta_1 + \beta_2 x_2 + \ldots + \beta_K x_K)$

$$\Pr(y=1|x) = G(\boldsymbol{x\beta}) \tag{4.1}$$

$$y_i = \begin{cases} 1 \text{ if the i} - \text{th person is visiting a healthcare provider} \\ 0 \text{ otherwise} \end{cases}$$

where x is the independent variables and G is a function taking on values strictly between zero and one: $0 < G(z) < 1$, for all real numbers z. The non-linear function of G is assumed to follow a logistic distribution:

$$G(\boldsymbol{x\beta}) = \frac{\exp(\boldsymbol{x\beta})}{1+\exp(\boldsymbol{x\beta})}$$

The dependent variable is whether a person seeks medical care by visiting a healthcare provider (visit=1) or not (visit=0), conditional to sickness symptoms. Included among the healthcare providers (visit=1) are hospitals (public and private), public health centres and auxiliary health centres, clinics and private physicians (GPs, specialists, dentists and family doctors), private practitioners (paramedics, nurses and midwives) and traditional providers. Included in the non-visit (visit=0) are other alternatives such as self-treatment, which includes buying over-the-counter medicine, treating the illness by coining or consuming herbal medicine, or forgoing any visit to any healthcare provider. A detailed description of these providers is given in Appendix 1.

In this study, the dependent variable is conditional on sickness symptoms. This condition is used as it reflects natural healthcare-seeking behaviour and serves as a standard of health need, ensuring fairness between samples. Sickness is measured by self-reported data and consequently could create an association with healthcare use (endogeneity) and may suffer selection bias. However, a study by Hidayat (2008) found that conditional estimates in IFLS data do not suffer from statistical bias.

Various independent variables were introduced into the model deliberately for explanatory purposes. Yet, a boundary to limit the number of variables was necessary to reduce the standard errors possible. The models were built on the framework of the behaviour model of health service use (Andersen, 1995), consisting of predisposing, disposing and health need factors. However, in this study, the terms used for categorising independence are more conventional, including demographic characteristics; social structure; personal, family and community resources and healthcare need. The theoretical framework underpinning the model is described in Chapter 3.

In the Children model, four additional variables were introduced: carer's age, carer's employment status, carer's education level and number of children in the household. Other variables such as marital status and householder status are not relevant, while insurance subscription, facility knowledge and chronic disease information are not available in the questionnaires. Education level is highly correlated with age, and number of children in the household is highly correlated with household size. Therefore, education level and household size were dropped as variables.

In the Elderly model, chronic disease status (whether an individual is professionally diagnosed with at least one type of chronic disease) was added as a variable. This variable was dropped from the Adult model, as data is not available for respondents aged less than 40 years. Including it in the Adult model would reduce the size of the sample significantly. The description of the variables for each main model is provided in Table 4.1.

Table 4.1 Description of variables for the logistic regression of the three main models

Variable	Description	Children (<15 yrs) Mean	Children (<15 yrs) SD	Adult (15–69 yrs) Mean	Adult (15–69 yrs) SD	Elderly (70+ yrs) Mean	Elderly (70+ yrs) SD
Healthcare utilisation	1 if visited a healthcare provider in the last 4 weeks, 0 otherwise	0.287	0.452	0.181	0.385	0.261	0.439
Demographic							
Age	age in years	5.99	4.23	36.6	14.5	75.9	5.0
Sex	1 if female, 0 male	0.485	.500	0.539	0.498	0.546	0.498
Marital Status	1 if currently married, 0 single/widowed/divorced	—	—	0.680	0.446	0.502	0.500
Householder status	1 if the head householder, 0 otherwise	—	—	0.344	0.475	0.654	0.476
Religion	1 if Islam, 0 otherwise	0.896	0.304	0.890	0.312	.880	0.326
Ethnicity	1 if Javanese, 0 otherwise	0.381	0.491	0.413	0.492	0.435	0.496
Household Size	The number of members in the household (1, 2, 3 …, 15+)	—	—	6.699	2.972	6.122	3.214
Number of children	The number of children <15 years in the household	2.05	0.78	—	—	—	—
Social Economic							
Education	highest education level attended						
No education	1 if no education, 0 otherwise	—	—	6.78	—	46.57	—
Primary	1 if primary school, 0 otherwise	—	—	38.21	—	43.60	—
Secondary	1 if secondary school, 0 otherwise	—	—	46.50	—	8.80	—
Tertiary	1 if tertiary or higher, 0 otherwise	—	—	8.51	—	1.02	—
Facility knowledge	number of health facility locations known by respondent (0,1, …,10+)	—	—	5.551	1.865	4.652	2.065
Working	1 if currently working, 0 otherwise	—	—	0.390	0.487	0.640	0.480
Insured	1 if subscribed to health insurance, 0 otherwise	—	—	0.254	0.435	0.285	0.452
Economic status: Adjusted monthly household consumption (Rp million)	1st quartile	0.738	0.175	0.644	0.196	0.537	0.218
	2nd quartile	1.282	1.771	1.213	0.166	1.192	0.218
	3rd quartile	2.065	3.016	1.950	0.290	1.954	0.171
	4th quartile	5.099	3.397	4.685	3.040	4.378	0.293
Place of residence	1 if rural, 0 urban	0.457	.499	0.497	0.500	0.554	0.497
Island of residence	1 if Java or Bali island, 0 otherwise	0.601	.489	0.610	0.488	0.641	0.480
Health needs							
Self-rated health	1 if health condition is poor, 0 good	0.148	0.355	0.176	0.381	0.395	0.489
Severity of illness	1 if at least 1 day staying in bed due to illness in the last 4 weeks, 0 none	0.551	0.497	0.409	0.491	0.500	0.500
Chronic disease	1 if diagnosed with at least one chronic disease by medical doctor, 0 otherwise	—	—	—	—	0.464	0.498
Carer Characteristics							
Carer's age	the age of the carer (year)	34.7	23.3	—	—	—	—
Care's sex	the sex of the carer (0 if male 1 female)	0.94	0.24	—	—	—	—
Carer's education	the education level of the carer (0 no education, 1 primary, 2 secondary , 3 tertiary or higher)	1.67	0.70	—	—	—	—
Sample (N)		**8,316**		**14,775**		**753**	

B.2. Diagnostic Test

A series of diagnostic tests were conducted to examine the model specification. The tests included a link test to examine the adequacy of the independent variable specification (Pregibon, 1981) and a Box-Tidwell test (Box and Tidwell, 1962) to explore possible transformations of continuous-type independent variables. The goodness of fit of the model was evaluated by investigating the predicted probability method using a Hosmer-Lemeshow test (Hosmer et al., 1988). The model was also checked against multicollinearity by evaluating its variance inflation factors (VIF). Details of the diagnostics are presented in Appendix 2.

The inclusion of health insurance subscription posed a possible adverse selection problem. Certain individuals with unobserved characteristics might self-select into insurance programs (Waters, 1999). For example, an individual with a high risk of illnesses might tend to seek healthcare more and thus be more likely to subscribe to health insurance. Thus, this factor could represent an endogeneity problem in the model. Testing for endogeneity is important. Ignoring the potential endogeneity of insurance membership could lead to a biased interpretation of the responsiveness of demand for healthcare to insurance and price. On the other hand, when endogeneity does not present, correcting it results in a larger standard error and reduced precision (Manning et al., 1987, Newhouse et al., 1974).

In Indonesia, as reflected in the 2007 IFLS, there are three main insurance schemes, depending mainly on the sector in which a person works and their welfare category. Private health insurance is voluntary. Askes (for civil servants) and Asabri (for military force) are mandatory, Jamsostek (for formal sector worker) is mandatory to some extent, and Askeskin is a social health insurance for the poor, with the premium paid by the government. In the Adult and Elderly models, all three insurance subscription types are collapsed into one category (that is, having insurance subscription) for simplicity. The effect of collapsing these insurance schemes on the decision to visit a healthcare provider is expected to be minimal because the dependent variables are also a collapsed category from private and public healthcare providers.

The potential endogeneity of insurance in this study arises from the fact that private insurance is voluntary or only partially mandatory, reflecting a potential for selection bias elements. Even in the case of the fully mandatory insurance (Askeskin), those who subscribe to this insurance might have unobserved characteristics that distinguish them from the rest of the sample.

Previous studies in other countries have found mixed results on insurance selection bias. Several studies found the presence of endogeneity on one partially mandatory insurance program, but no selection bias for voluntary programs in Ecuador (Waters, 1999). Another study found endogeneity in a voluntary insurance program in Mexico (Sosa-Rubí et al., 2009), while a study in Columbia (Trujillo, 2003) found mixed results of selection bias of insurance related to health status. A study in China simply assumed the non-existence of endogeneity when health insurance is not voluntary (Qian et al., 2009).

In the context of Indonesia, a study by Hidayat (2008) using the 1997 wave of the IFLS did not detect endogeneity in the three types of health insurance. Using a multinomial model, that study showed that health insurance (Askes and Jamsostek) is exogenous to choice of private or public provider, both for conditional (those who have prior symptoms of illness) and unconditional samples (regardless of illness symptoms).

Following Waters (1999), three instrumental variable-based methods and a likelihood ratio test were employed to assess the significance of the impact of health insurance on identifying variables to health visits. The test of endogeneity showed that health insurance is exogenous (*rho* = -0.226, *p-value* = 0.2191). This result is in line with the study by Hidayat (2008). More details on this endogeneity test are presented in Appendix 3.

The exogeneity of health insurance is partly explained by the fact that most insurance subscriptions are not voluntary, but are assigned based on working and social economic status. For example, among the adult sample in the 2007 IFLS, only 5.6% were subscribed to voluntary health insurance. Therefore, potential self-selection bias is minimal. Another possibility is that, in this study, health visits are restricted to outpatient visits. In most cases, the price of service for outpatients is relatively small as compared to inpatient visits, and therefore the role of insurance in reducing the financial barrier to health service use is likely small.

C. Result of Model Estimations

The logistic model of Adult 15+ (that is, the model that does not distinguish between trajectories for adults and the elderly) is provided in Appendix 4. The estimation of the logit of the Adult 15+ model shows that, in general, demographic, social economic and health need factors are influential in healthcare utilisation. Healthcare utilisation increases with age and females are more likely to utilise healthcare. The odds ratio presented in the regression estimation is the odds ratio at sample mean. In the case of age, the odds ratio of 1.006 is at age 36.6 years (the mean age of the adult sample). This should be noted cautiously, as a bivariate description of healthcare utilisation trends (Figure 4.1) show that at age 70 and above, utilisation decreases by age. The different trend between adults and the elderly is not shown clearly in the estimate.

In a population in which a change is expected in the size and structure of the elderly cohort, a separate model for the elderly (age 70 and above) is beneficial for investigating utilisation patterns in this age group. This justifies the need to separate the elderly (70 years and above) and the adult (15–69 years) samples. Further, the independent variables may affect utilisation differently in the elderly (Wolinsky et al., 1986).

Table 4.2 shows the three separate models built for each stage of life: Children, Adult and Elderly. The regression estimations of the three models provide a strong indication that the list of determinants laid out in Andersen's framework influences utilisation differently between children, adults and the elderly. Age is a significant factor for children and adults, but not for the elderly. The effect of sex among adults is significant, but it is only marginally influential among children and the elderly.

Table 4.2 Estimates of logistic regression of healthcare utilisation for the Children, Adult and Elderly models

Variable	Model					
	Children (<15 yrs)		Adult (15–69 yrs)		Elderly (70+ yrs)	
	Odds ratio	SE	Odds ratio	SE	Odds ratio	SE
Demographic						
Age	0.889***	0.020	1.006***	0.011	1.283	0.895
Age square	1.002	0.002	1.000	0.000	0.998	0.005
Sex	0.898*	0.048	1.691***	0.106	1.907*	0.531
Marital status			1.415***	0.086	1.139	0.274
Householder status			1.161*	0.080	1.269	0.303
Religion	1.027	0.094	1.021	0.077	1.318	0.393
Ethnicity	0.959	0.057	1.019	0.052	0.899	0.194
Household size			0.996	0.008	0.955	0.032
Number of children	0.882***	0.031				
Social Economic						
Education:						
No education			Ref.	—	Ref.	—
Primary			1.374***	0.137	1.235	0.258
Secondary			1.388**	0.151	1.533	0.554
Tertiary			1.521***	0.200	2.283	1.899
Facility knowledge			1.074***	0.015	1.136**	0.059
Working			1.198***	0.062	0.676	0.143
Insured			1.429***	0.073	1.455	0.287
Household income:						
1st Quartile (lowest)	Ref.	—	Ref.	—	Ref.	—
2nd Quartile	1.165*	0.102	1.116	0.078	1.327	0.334
3rd Quartile	1.456***	0.126	1.333***	0.095	2.107**	0.598
4th Quartile (highest)	1.354**	0.123	1.347***	0.102	1.268	0.422
Place of residence	0.837**	0.048	1.172**	0.059	1.256	0.253
Island of residence	1.495***	0.090	1.150**	0.061	1.042	0.228
Health need						
Self-rated health	1.725***	0.120	1.907***	0.103	1.125	0.231
Severity of illness	3.663***	0.220	2.996***	0.144	2.752***	0.551
Chronic disease					2.679***	0.528
Carer's Characteristics						
Carer's age	0.931	0.059				
Carer's sex	0.951	0.113				
Carer's education	1.103**	0.048				
Carer's employment	0.942	0.054				
Constant	0.246***	0.059	0.012***	0.003	0.000	0.000
Sample (N)	**8,316**		**14,775**		**753**	

Notes: Significant level: *** $p<0.001$, ** $p<0.01$, * $p<0.05$

For the Adult and Children models, the sample sizes were quite big, resulting in the statistical significance of the coefficient of regression to almost all of the variables. A substantive significance can be evaluated using standardised regression. Heise (1969) suggested that, to be considered substantively significant in a large survey, a standardised regression coefficient must be greater or equal to approximately 0.10. In general, the models show that health need variables are among the most significant. Other variables with significant effects are age, sex among adults and the elderly and island of residence among children. Detailed results of the standardised logistic regressions of the Children, Adult and Elderly models are provided in Appendix 5.

Previous studies indicate that among children, the role of parents or carers, especially the past record of the mother's healthcare-seeking behaviour, are significant (Janicke et al., 2001), reflecting the naturally high attention of parents to their younger children (Riley et al., 1993). In this study, mother's education level is influential to the utilisation of healthcare. Mother's age, sex, marital status and employment, however, do not have a significant effect on utilisation. Unfortunately, the effect of mother's past healthcare-seeking behaviour cannot be determined in the absence of such information in the 2007 IFLS.

Among adults, most of the demographic, social economic and health need factors are influential to the decision to utilise healthcare, with the exception of religion, ethnicity and household size. Among the elderly, severity of illness and chronic disease are influential, while most of the remaining variables are not. This result is consistent with the previous study by Rosner (1988) in the US that found that income and severity of illness were the only two variables with direct causal effects on healthcare utilisation among the elderly.

The above estimations confirm a non-monotonic effect of age on utilisation. Consequently, including the elderly in the adult model could be misleading because of the sample size effects (95% adult and 5% elderly) in the Adult 15+ model. Therefore, for the elderly population, a separate model provides a better fit.

C.1. The Effects of Sex

The effects of sex vary by age group. Females are more likely than males to seek medical care as adults and elderly. Among children, boys are more likely to use medical care than are girls, although the effect is marginal (see Figure 4.3). Higher standard error among the elderly is probably due to the smaller sample size (753 respondents).

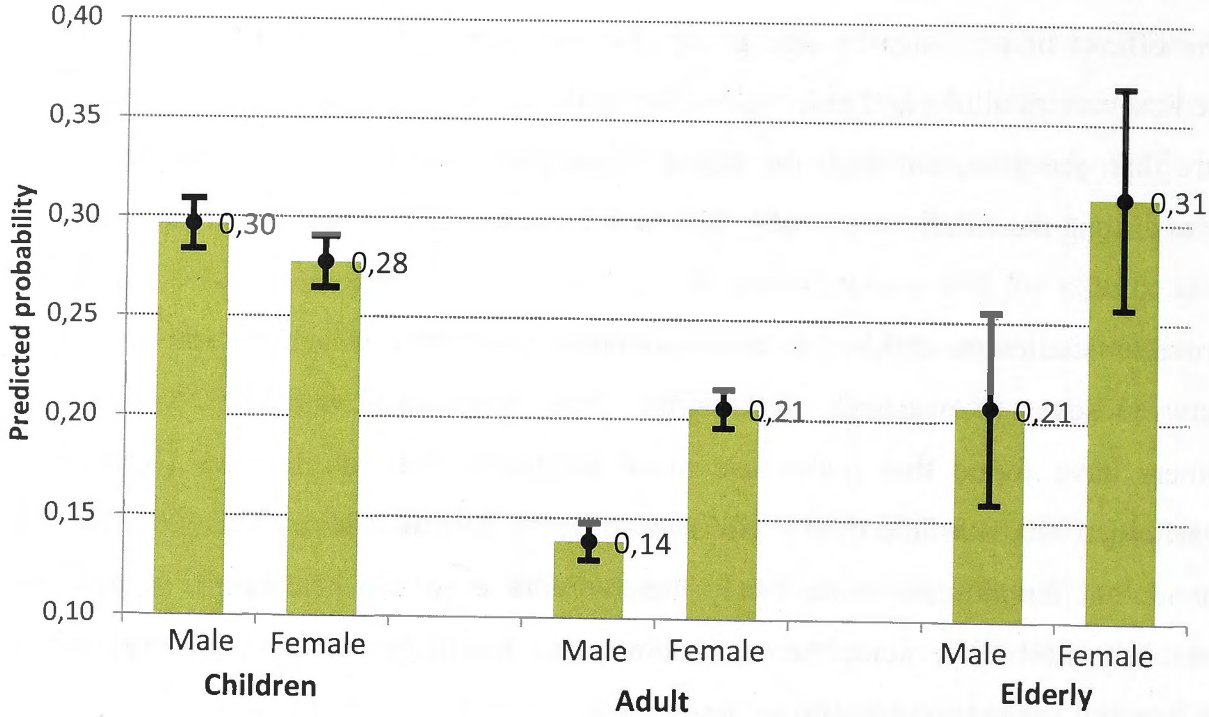
Previous studies on children in other countries show that utilisation was not different between sexes (Newacheck and Halfon, 1986, Horwitz et al., 1985, Wolfe, 1980). Others have found that males use more healthcare than do females (Kelleher and Starfield, 1990, Starfield et al., 1985). A study by Palacio-Vieira et al. (2012) in Spain found that females are more likely than are males to use healthcare. In that study, persistent morbidity, mental health problems and familial patterns of use explained this differential in the use of health services.

Higher use among females during adulthood reflects previous studies, which have consistently documented higher utilisation among females (Stevens et al., 2012, Verbrugge and Wingard, 1987, Hibbard and Pope, 1983, Cleary et al., 1982). In this model, outpatient visits for prenatal purposes were excluded from the model. Hence, the higher utilisation among females is not due to maternal-related visits.

Among the elderly, the odds ratio of utilisation among females is 29% higher than for males. This is consistent with previous studies conducted in many other countries, including Norway and Finland (Suominen-Taipale et al., 2006), Jamaica (Bourne, 2009), Senegal (Lepine and Le Nestour, 2011) and other parts of the world. For the Indonesian case in this study, again, it is important to note that high variability due to the limited size of the sample might affect the result of the logistic estimation. Another data source with a bigger sample size (2007 Susenas) will be considered in Chapter 8 to investigate the effects of sex and age, to project healthcare in the future.

The effects of sex can also be observed by predicting the probability of utilising a healthcare provider among children, adults and the elderly by sex. These are provided in Figure 4.3 along with their 95% confidence interval bands. The figure shows that the effect of sex is quite strong among adults and the elderly, but not among children.

Figure 4.3 The predicted probability of healthcare utilisation among children, adults and the elderly by sex, with 95% confidence interval



The effect of sex is quite strong with the standardised coefficient of 0.13, seconded only by the severity of illness with a standardised coefficient of 0.27. Previous studies have offered the explanation that this sex differential comes from biological differences (Phillips, 2005, Mustard et al., 1998), health perceptions and self-reporting behaviour (Waldron, 1983, Hibbard and Pope, 1983). The difference has also been associated with healthcare expenditure (Bertakis et al., 2000), but can vary according to particular symptoms and the phase of life cycle (Macintyre et al., 1996). A growing literature suggests that social economy determinants play an important role in the perception of illness and subsequent healthcare behaviour. Among the elderly, one important factor that affects the utilisation of care is the nature of his or her chronic disease (Mutran and Ferraro, 1988). Del Mar García-Calventė et al. (2012) suggests that in using healthcare, males use biological arguments, while females use cultural models, and are influenced by social stratification, gender roles and power imbalances.

To identify the relative roles of the determinants, two separate logistic regressions were developed (for Adult 15+ males and females, respectively) using the shared variables used in the Children and Adult models, with the exception of sex. The resulting estimates from the regression can be used to assess the relative degree of effects of determinants (see Table 4.3). For the elderly, the effect of sex is strong (but with a wide band of confidence interval) and further separation of models for elderly males and females may suffer from high standard errors due to small sample size (341 males and 411 females). Therefore, no such separate models were created for this cohort.

Table 4.3 Summary of the degree of effects of independent variables on utilisation of healthcare provider between males and females among children and adults

Variable	Model			
	Children (<15 yrs)		Adult (15–69 yrs)	
	Male	Female	Male	Female
Demographic				
Age	—-	—	+++	+++
Age square	0	0	0	0
Marital status	n.a	n.a	0	+++
Householder status	n.a	n.a	0	+++
Religion	0	0	0	0
Ethnicity	0	0	0	0
Household size	n.a	n.a	0	0
Number of children	-	-	n.a	n.a
Social Economic				
Education:				
No education	n.a	n.a	Ref	Ref
Primary	n.a	n.a	+++	0
Secondary	n.a	n.a	+++	0
Tertiary	n.a	n.a	+++	0
Facility knowledge	n.a	n.a	++	+++
Working	n.a	n.a	0	++
Insured	n.a	n.a	+	+++
Economic status				
1st Quartile (lowest)	Ref	Ref	Ref	Ref
2nd Quartile	++	0	0	0
3rd Quartile	+++	+	0	+++
4th Quartile (highest)	++	0	0	++
Place of residence	0	—	0	++
Island of residence	+++	+++	0	+
Health need				
Self-rated health	+++	+++	+++	+++
Severity of illness	+++	+++	+++	+++
Carer's characteristics				
Carer's age	0	0	n.a	n.a
Carer's sex	0	0	n.a	n.a
Carer's education	0	0	n.a	n.a
Carer's employment	0	0	n.a	n.a

Notes: +++: Positive significant ($p<0.001$); ++: Positive significant ($p<0.01$); ++: Positive significant ($p<0.05$); —-: Negative significant ($p<0.001$); —: Negative significant ($p<0.01$); -: Negative significant ($p<0.05$); 0: Not significant; n.a: not available (not included in the model)

Table 4.3 shows that the effects are mostly similar in terms of degree of significance, except for household economic status. Since sex effects among children are marginal, the similarities in the effect of the variables in both models are expected. For the Adult model, however, the pattern of determinants is quite different between males and females, suggesting a strong role for social, economic and cultural factors among females. For both male and female adults, health needs affect utilisation significantly, whereas religion, ethnicity and household size do not. Other than these, all variables are significant determinants of adult females' utilisation, with the exception of education. These results mostly support the findings of Del Mar García-Calvente et al. (2012), who found that females' utilisation is influenced more by social stratification, gender roles and power imbalances than by biological determinants.

Marriage has a positive effect on healthcare utilisation by both males and females. The average probability of utilisation for unmarried females and males is 0.11 and 0.17 respectively; while for married males and females it is 0.15 and 0.22, respectively. Even though the married females are more likely than are married males to utilise healthcare, the gain of probability relative to initial value due to marriage is higher among males (36%) than among females (29%).

Another marked difference is in householder status. Being the head of the household increases the probability of utilising a healthcare provider by 7.3 percentage points (p <0.001) among females, but is not significant (0.7%, p-value=0.315) among males. This might be related to the fact that being a head of household enables females to assume a greater role, already assumed by males, in decision making and command over resources, eventually enabling them to seek medical care (Bloom et al., 2001). Other social and economic factors such as working status, health insurance subscription, place of residence, island of residence and household income are significant among females but insignificant among males.

Even though effects of some social and economic factors are relatively small individually, the interaction effects with other factors can be significant. For example, being employed, having a higher income and being a household head increased the likelihood to visit significantly among females, but not among males. These interactions could be useful, for example, if further effects of social economic change are simulated to predict their effects on healthcare utilisation. Table 4.4 is an illustration of how the different hypothetical social economic statuses (A, B and C) affect healthcare utilisation.

Table 4.4 Predicted probably of healthcare utilisation rate based on social economic status scenarios

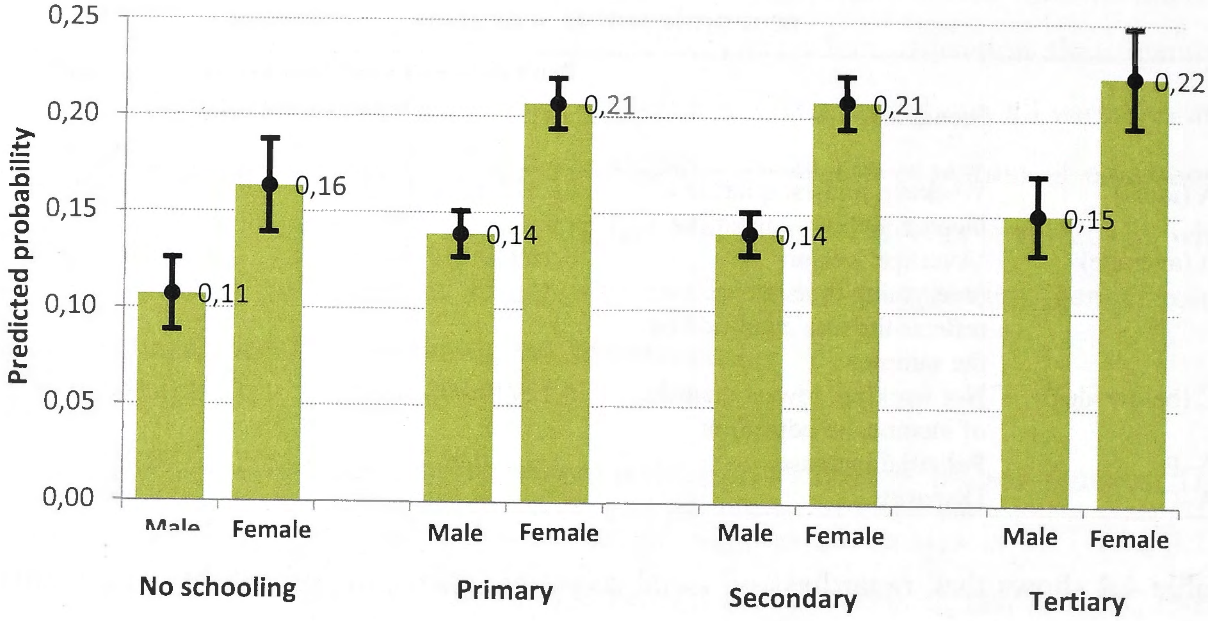
Scenarios		Probability of visiting a healthcare provider [95% confident interval]	
		Female	**Male**
A (ideal)	Working, highest quartile of income, tertiary education	0.232 [0.206–0.257]	0.139 [0.121–0.158]
B (average)	'Average' person (everything in its mean, reflects the true condition of the sample)	0.169 [0.159–0.178]	0.098 [0.09–0.106]
C (below ideal)	Not working, lowest quartile of income, no education	0.129 [0.108–0.139]	0.071 [0.060- 0.081]
A–B	Potential increase	0.063	0.041
A–C	Disparity	0.108	0.069

Table 4.4 shows that, regardless of social economic status, the probability of utilising a healthcare provider among females is higher than among males. However, the disparity (A–C) is relatively higher among females. If each of the scenarios is associated with a level of social economic status, and the potential increase (A–B) is interpreted as a gain from increased social economic status, then the effect of social economic status will be higher among females than among males.

Different from the other variables, education level affects the utilisation among males, but not females. This difference is mostly in the endowment value (in this case, the probability of healthcare utilisation for those who have no formal education) and is significantly lower among males than among females. The probability of utilising healthcare among males with no schooling is 0.062 (95% CI: 0.049–0.076), which is lower than among females without an education level, at 0.169 (95% CI: 0.149–0.170) (see Figure 4.4). Thus, the leverage of education among men can be seen as stronger.

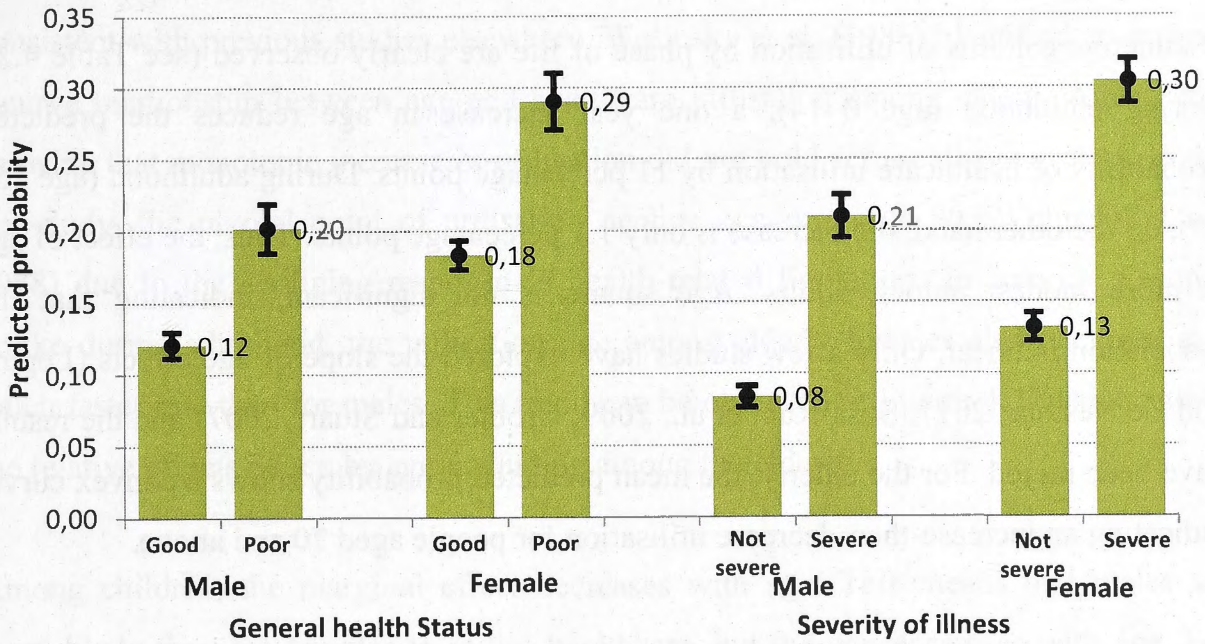
In Indonesia, females are exposed more to health education programs and awareness campaigns, primarily through health centres and *Posyandu*. This results in improved healthcare-seeking behaviour among females, regardless of formal education attainment. In fact, up until now, the Government of Indonesia has developed various programs focusing on mother and child health, from which women can gain knowledge, build their awareness and maintain their healthcare-seeking behaviour.

Figure 4.4 Predicted probability of utilising healthcare by education for males and females with 95% confidence interval



The effects of general health status are quite significant, but are not different between males and females. Poorer health increased the probability of utilising a healthcare provider by 7.0 percentage points among males and 9.6 percentage points among females. Severe sickness increases the probability of healthcare utilisation by approximately 14 percentage points for both males and females (see Figure 4.5).

Figure 4.5 Predicted probability of utilising healthcare services by general health status and severity of illness for males and females, with 95% confidence interval



Region of residence (living in an urban or rural area) has a significant effect on utilisation. Utilisation among females residing in rural areas is 2.6 percentage points higher ($p<0.01$) than for females living in urban areas. This might be explained by the fact that people in urban areas have easier access to self-treatment (which in this model is not categorised as utilising a healthcare provider). When over-the-counter medicine is easily available in a person's neighbourhood, for light symptoms of illness, women may forgo visiting a healthcare facility, which requires more effort both physically and financially. However, similar effects cannot be found among males, where healthcare service utilisation in urban and rural areas is the same.

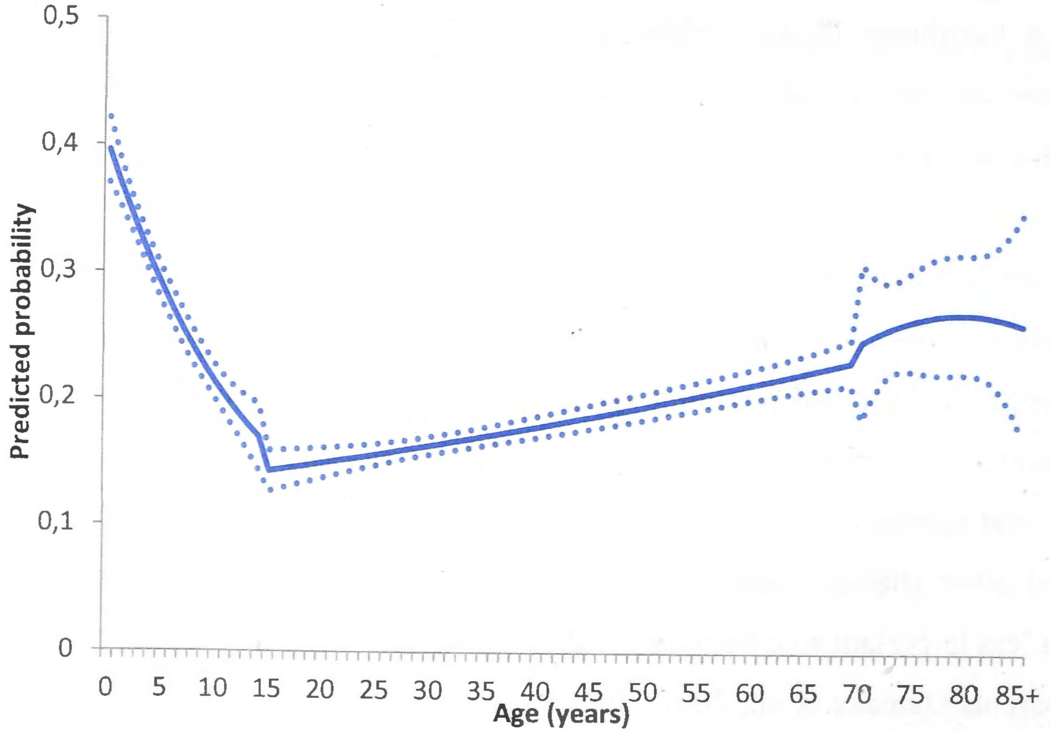
Referring to a study by Del Mar García-Calvente et al. (2012), the static preference of utilisation among males is related to biological factors, which make males less responsive to social, culture and economic factors. It is possible that males and females respond differently to problems of physical accessibility to healthcare facilities, such as travel distance and quality of service, both of which are marked distinctively between Java/Island and other islands. Among children, the 'biological' characteristics of the children play a less important role because the decision to seek medical care is primarily taken by the parents (Janicke et al., 2001). Parents on Java/Bali are more likely to take their children to health facilities because they are more accessible. A RPL will be employed to delve into the issues of accessibility in Chapter 6.

C.2. The Effects of Age

Distinctive patterns of utilisation by phase of life are clearly observed (see Table 4.2). During childhood (age 0–14), a one year increase in age reduces the predicted probability of healthcare utilisation by 11 percentage points. During adulthood (age 15–69), on the other hand, the increase is only 1.1 percentage points. Thus, the effect of age is more modest among adults. Age square is not significant, indicating that the association is linear. Only a few studies have explored the slope of age effects (Lepine and Le Nestour, 2011, Sosa-Rubí et al., 2009, Grobler and Stuart, 2007) and the results have been mixed. For the elderly, the mean predicted probability shows a convex curve, indicating an increase-then-decrease utilisation for people aged 70 and above.

The decreasing utilisation during childhood is common in other countries, as has been identified by Riley et al. (1993). A high rate of utilisation in the early years reflects the high attention of parents to their younger children. The positive association between utilisation and age during adulthood is also consistent with previous findings (Qian et al., 2009, Hidayat, 2008, Lance, 2003, Sahn et al., 2003).

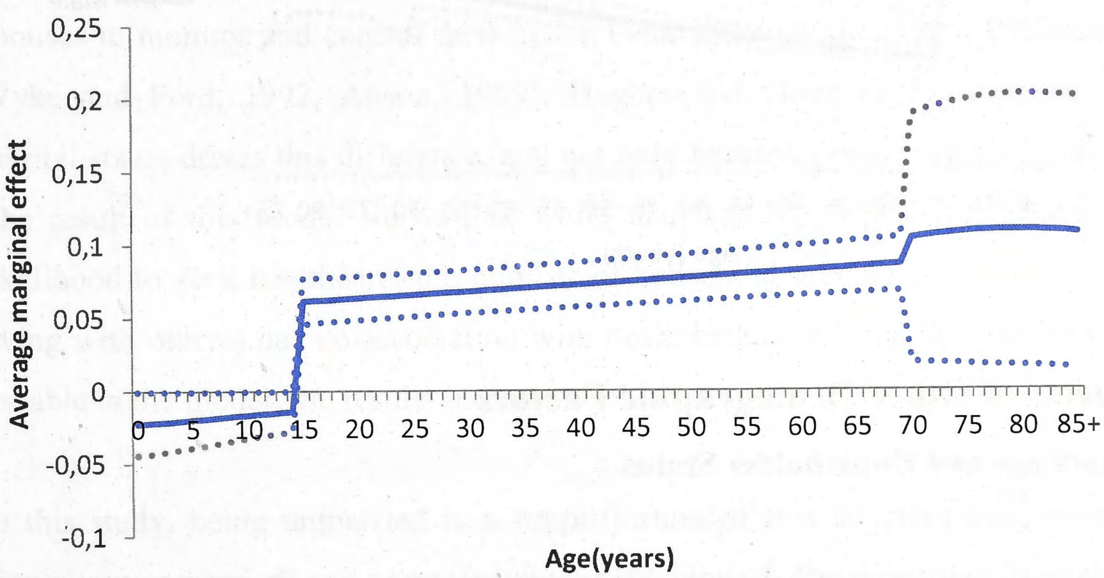
Figure 4.6 Predicted probability of healthcare utilisation by age among children, adults and the elderly, with 95% confidence interval



The pattern of utilisation changes when people enter old age. First, the likelihood of utilising healthcare starts to decline as people reach a very old age. This result is consistent with previous studies elsewhere. Wolinsky et al. (1986) identified an inverse J-curve relationship between age and healthcare utilisation among elderly Americans, showing that monotonic increase of utilisation did not hold across all age groups. In the US study, the pivotal point of utilisation decline occurs at age 80 (Wolinsky et al., 1988) due to the declining response to health-related limitations in activity. Second, unlike during adulthood, the utilisation rate among elderly females also declines, at a much faster rate than for males. This trend can be observed in Figure 4.7, which shows the relative effects of sex by age, including among the elderly.

Among children, the marginal effect decreases with age. This means that males are more likely than are females to utilise healthcare, but the gap decreases with age. For adults, females are more likely to visit healthcare providers than are males at all ages, with the marginal effect of sex increasing with age. At age 15, for example, females are 6.1 percentage points more likely than are males to seek medical care, and at age 69, the probability increases to 8.6 percentage points.

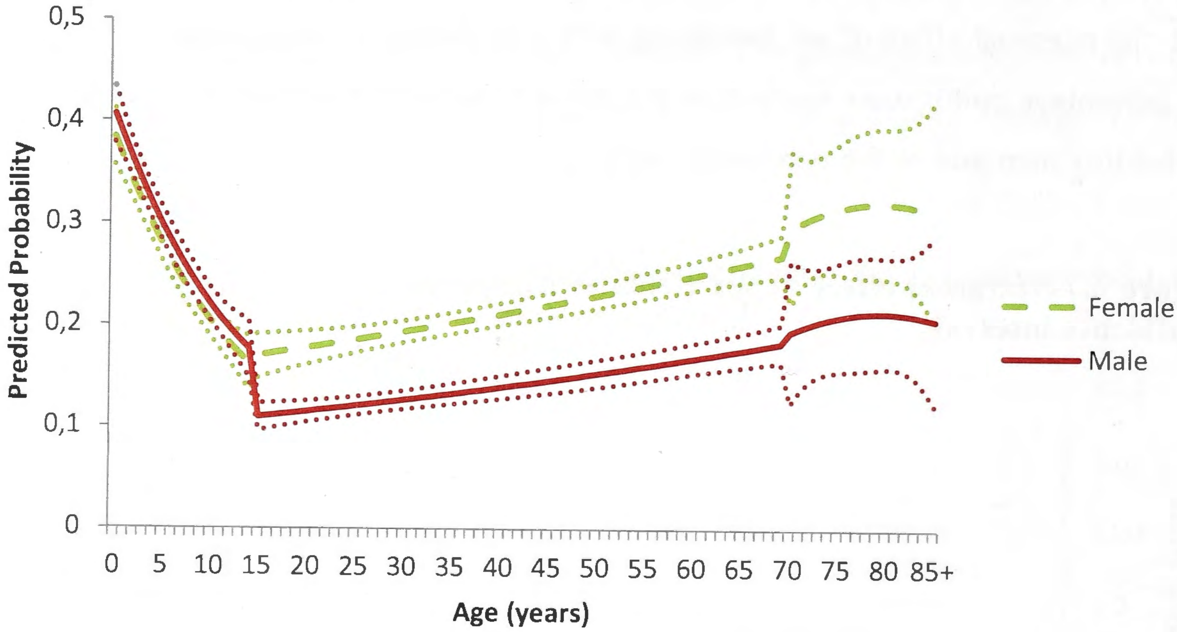
Figure 4.7 Marginal effect of sex (females compared to males) by age, with 95% confidence interval



As for the elderly, females are still more likely to seek medical care. However, it is difficult to conclude the effect of age even though the mean values show a convex curve. Susenas data can give a clearer picture. The trend of utilisation among the elderly decreases with age (see Chapter 3, Figure 3.8), with the decline among females more rapid than for males. The decline utilisation among the very old is caused by a declining response to sickness, the loss of long-standing contact with a physician, or because the physician of the patient thinks that treatment is of no further benefit (Wolinsky et al., 1988). Another possible explanation includes the population cohort effect, or simply a 'natural selection', in which the very old population with a higher rate of sickness declines due to their higher mortality rate.

The effect of age among males and females on utilisation can also be presented in predicted probability so that the difference between males and females can be visually compared (see Figure 4.8).

Figure 4.8 Predicted probability of utilising a healthcare provider among males and females by age, with 95% confidence interval band



C.3. Effects of Other Demographic Factors

C.3.1. Marriage and Householder Status

Marriage has a significant association with healthcare utilisation. On average, the odds of utilisation by a married adult are 1.415 ($p<0.001$) times as high as for an unmarried adult. Among the elderly, the effect of marriage is also positive, but not significant. One of the mechanisms is through economic resources. Generally, a married person has more access to economic resources (Ross, 1995, Ross et al., 1990), which enables him or her to access healthcare. In this study, however, other mechanisms may be at work, as income as an indicator of economic resources has been controlled.

In the 2007 IFLS data, the income profile of married and unmarried persons is quite similar. The average monthly household income of a married person is Rp 2.53 million, and for an unmarried person it is Rp 2.49 million. The range and distribution among quintiles is also similar. If income is the driver for married persons to utilise higher healthcare, the utilisation for married persons will not increase when income remains the same. In fact, this is not the case. Table 4.5 shows that in every income quartile, the probability of healthcare utilisation for those who are married is consistently higher.

Table 4.5 Predicted probability of healthcare utilisation by income level and marital status

	Predicted probability of healthcare utilisation	
Income quartile	Married	Not married
Q1 (lowest)	0.1306 [0.1197–0.1414]	0.0925 [0.0822–0.1028]
Q2	0.1416 [0.1336–0.1496]	0.1007 [0.0915–0.1099]
Q3	0.1534 [0.1451–0.1617]	0.1095 [0.0997–0.1193]
Q4 (highest)	0.1660 [0.1534–0.1785]	0.1190 [0.1065–0.1316]

Another possible explanation is that marriage grants individuals access to more social resources, such as emotional support and mutual monitoring, which in turn enable their spouses to monitor and control their health behaviours (Waite, 1995, Umberson, 1992, Wyke and Ford, 1992, Anson, 1989). Hughes and Gove (1981) demonstrated that marital status drives this difference, and not only because people are living with others. The result of this model shows that while marriage has a positive influence on the likelihood to seek healthcare, the number of household members (which is a proxy of living with others) has no association with healthcare behaviour. Although not directly testable in the model, the results indicate a role for social support because of marriage.

In this study, being unmarried is a simplification of two different categories; that is, single (never married) and separated/divorced/widowed. By expanding marital category into never married, married and divorced/widowed/separated, it is found that marriage increases the odds of healthcare utilisation by 60% (p-value <0.001) compared to never married. Being a widow/divorced/separated increases the odds by 26% (p-value <0.05) compared to never married; but decreases the odds by 23% (p-value <0.01) compared to being married.

This trend is an indication of individual behavioural change due to marital transition, by which utilisation of healthcare increases from single (never married) into married, and then decreases upon the end of marriage. Although these transitions (longitudinally) occur in the US (Umberson, 1987), this study is based on a cross-sectional survey. Therefore, further study is necessary to investigate whether this behavioural change occurs in parallel with marital transition in a longitudinal data context.

Being the head of the household significantly increases the probability of visiting a healthcare provider. Further analysis shows, however, that the effect is only significant for females and not for males. The different health behaviour between the head of the household and the other family members might operate through the social and economic roles assumed by the head of the household. As the head of the household is responsible for carrying out most of the household's affairs, his or her health status is important and this subsequently increases the probability that he or she will seek medical care in the case of illness. The second explanation is that the head of the household has more power in disposing the available resources in the family for healthcare services.

C.3.2. Household Size

As a measure of wealth, family income can be different from individual income, especially for families with more than one household member. Therefore, it is necessary to standardise income with the number of members in the household using household size. Household size does not have any significant effect on healthcare utilisation. However, household size is an important factor to control household income. A likelihood ratio test shows that household size is important to control household income ($LRX^2 = 16.96$, $p <.01$). Referring to the suggestion by Hughes and Gove (1981) discussed above, household size is important since it determines the income per capita in the household. However, it is not significant if it is interpreted as an indicator of the intensity of living with others.

Previous studies have found mixed results on the influence of household size on healthcare-seeking behaviour. A study by Hidayat (2008), using data from 1997 IFLS, finds that effect of household size is not significant. Similar findings are also observed in Tanzania (Sahn et al., 2003) and South Africa (Grobler and Stuart, 2007). However, studies by Borah (2006), using data from rural India; Dzator and Asafu-Adjaye (2004) in Ghana; and Gotsadze et al. (2005) in Georgia found that household size has a significant association with healthcare utilisation.

For the Children model, the number of children in the household is negatively associated with healthcare utilisation (odds ratio 0.882, $p<0.001$), while the interaction effect between number of children and age is not significant. It is likely that many children require additional financial resources (for the same level of household income) from the parent or carer. This burden is compensated for by reducing efforts of taking them to a health facility when they are sick. The negative association between number of children in the household and healthcare utilisation has also been found in previous studies for children in the US (Newacheck and Halfon, 1986, Riley et al., 1993).

C.3.3. Ethnicity and Religion

Ethnicity and religion are factors that predispose a person to use a health service. Social norms and values influence the subsequent perceptions of need and use of health services (Andersen, 1995). Although not directly related to utilisation, the values conveyed in religion and ethnic character are related to other variables that may foster or prevent a person to seek medical care.

The results in this study show that neither ethnicity (Javanese and non-Javanese) nor religion (Islam and non-Islam) play a significant role in the decision to use health services. Wolinsky (1978) indicated that the minor effect of ethnicity and religion is related to the fact that predisposing factors do not directly affect the use of service but work through enabling and health need factors.

These variables are usually used to evaluate healthcare inequity by measuring systematic disparities among disadvantaged groups by virtue of ethnicity or religious affiliation (Braveman, 2006). In this study, the inequity of healthcare utilisation, holding other variables constant, does not present as a problem. There are no significant differences in healthcare utilisation between Muslims as the majority population and other religious groupings or between Javanese (the biggest ethnic population) and other ethnic populations.

C.4. Social Economic Factors

C.4.1. Education Level and Knowledge of Facility

Utilisation of healthcare services is positively associated with level of education, as shown by the increase in average marginal effect (AME) when level of education increases. This finding is consistent with most studies in Indonesia and other countries (Lance, 2003, Hidayat, 2008, Borah, 2006, Sahn et al., 2003, Qian et al., 2009). The effect of education is significant among males and not among females, probably due to the higher endowment value of healthcare-seeking behaviour among females through health education programs (see Chapter 4, Section C.1).

The effects of education may vary if the utilisation is differentiated by type of healthcare provider. For example, Lance (2003) shows that higher education level is associated with a higher utilisation of modern providers (doctors, clinics and health centres), but lower utilisation of paramedics, nurses and midwives. Hidayat (2008) also found the effect of education on utilisation of private providers to be significant, but this was not the case for public providers. Chapter 5 provides further discussion of the inclination towards utilisation of certain types of provider.

The 2007 IFLS asked respondents whether they knew the location of each of 10 types of health facility (public and private hospitals, health centres, private clinics and physicians, midwives, nurse paramedics, traditional practitioners, traditional birth attendants and *Posyandu* for the elderly). This variable is used in the model as a proxy to assess the impact of the knowledge of respondents on the available healthcare provider choices in their community. It is assumed that knowing more locations of available health facilities helps respondents to choose a provider, and subsequently increases healthcare utilisation.

The results indicate that high facility knowledge is positively associated with healthcare utilisation. On average, a one-point increase in the facility knowledge index increases the likelihood of visiting a healthcare provider by 7.4%. This knowledge index should be interpreted cautiously for potential of endogeneity. If people use a health provider location, people know that the facility exists.

From the supply perspective, the facility knowledge index may represent the extent of the availability and accessibility of healthcare providers in the community. With this in mind, higher accessibility leads to increased use of health facilities. This finding is similar to that found by Rokx et al. (2010). Further discussion on healthcare accessibility is provided in Chapter 6.

C.4.2. Employment and Income

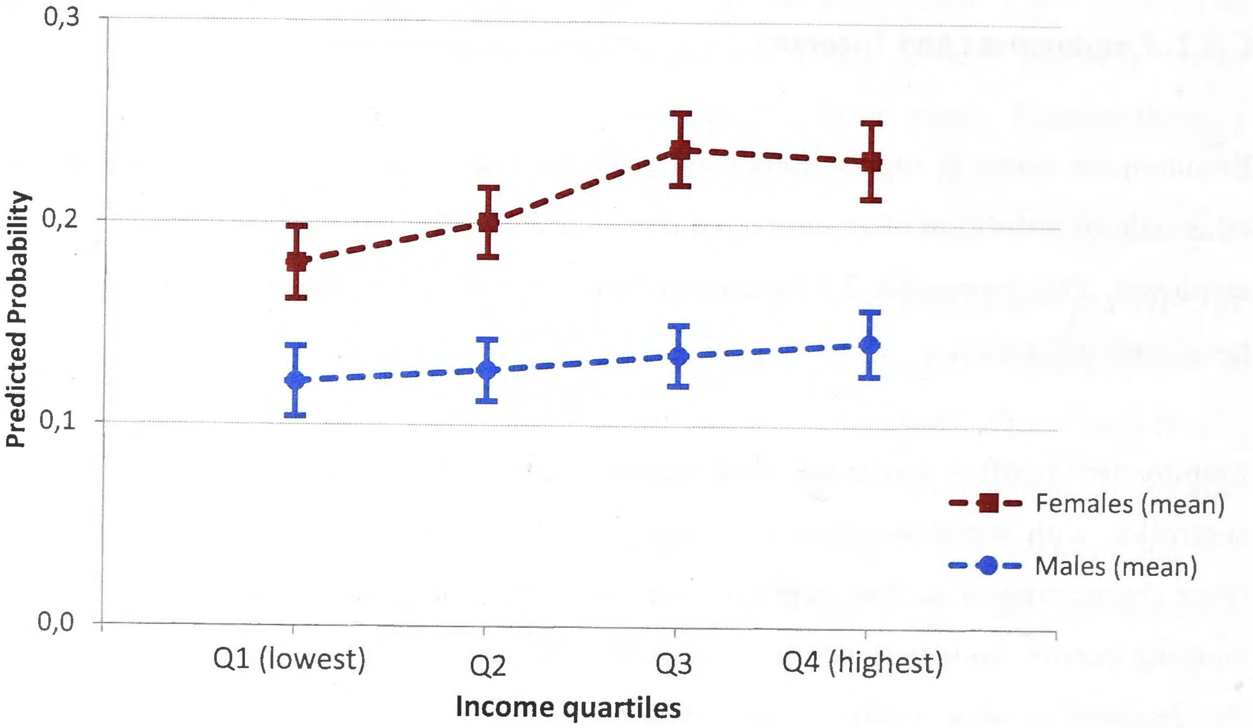
Employment status is highly associated with the likelihood to utilise healthcare. The odds ratio of utilisation of an employed person is 20.7% higher than a person who is not employed. This represents 2.3 percentage points ($p<0.001$) higher in the probability of healthcare utilization.

Employment is often associated with income and education. Since the model has been controlled with variables related to income and education, employment may reflect other characteristics such as peer pressure and higher opportunity cost of being sick. A working person tends to have more networks that may contribute as a social support in the decision to seek medical care (Andersen, 1995). In addition, being sick while employed may bear a higher opportunity cost due to forgone earnings. Seeking care is a mechanism to reduce forgone earnings (Hadley, 2003).

Household income has a significant influence on healthcare utilisation decisions. The odds ratios of utilising a healthcare provider for a person in a household within income quartile 3 (Q3) and 4 (Q4) are 33% and 35% higher than those in Q1, respectively. However, this same effect for households with a one-income quartile difference, such as from Q1 to Q2, Q2 to Q3, and so on, is not significant.

Females are more likely than are males to utilise healthcare at all levels of household income. When treated as a continuous variable,[16] an increase of Rp1 million in the household income increases the probability of utilisation on average by 1.9 percentage points among females and 0.7 percentage points among males (see Figure 4.9). The average income of the sample is Rp 2.46 million (standard deviation Rp 2.49 million) a month. Therefore, an increase of Rp 1 million in income is considered large among the general population. Consequently, the gain in utilisation due to increased income seems to be marginal in real terms. (Details of predicted probability are provided in Appendix 8).

Figure 4.9 Predicted probability of healthcare utilisation by income quartiles among males and females, with 95% confidence interval



For females, the effects of income from Q3 to Q4 diminish, indicating the decreased marginal value of money. The cost of outpatient care is generally low, and therefore the effect of income is more prevalent among the lower income category. This result might be different from the effect of income to inpatient visit, which is generally more expensive in terms of cost of services compared to outpatient visits.

[16] The similar logit model was run with a modification income variable. In the original model, dummies of income (four quartiles) are used. In the modified model, a continuous income variable (in 1 million rupiah) is used instead. Details of the model estimates are not shown here.

C.4.3. Place of Residence

By definition, urban Indonesia is differentiated from rural areas by its population density, proportion of households relying on agriculture for their livelihood and access to a variety of public facilities such as markets, hospitals and schools. Beyond this technical definition, there are considerable social, economic and cultural differences between urban and rural communities. Lance (2003) went even further by assuming that the structure of health services in urban areas is fundamentally different from those in rural areas. For example, healthcare services in rural areas are dominated by public health centres and sub-health centres. Therefore, in this study, two different models were developed, for urban and rural areas.

The 2007 IFLS data shows a marked difference between rural and urban areas in provider choice; in particular, in utilisation of nurses, midwives, paramedics and physicians. However, for overall healthcare utilisation, the patterns are similar (see Table 4.6). Further, the analysis of healthcare utilisation does not differentiate type of utilisation, and therefore, in this chapter, urban–rural is introduced as an independent variable and not as the basis for separating into rural and urban models.

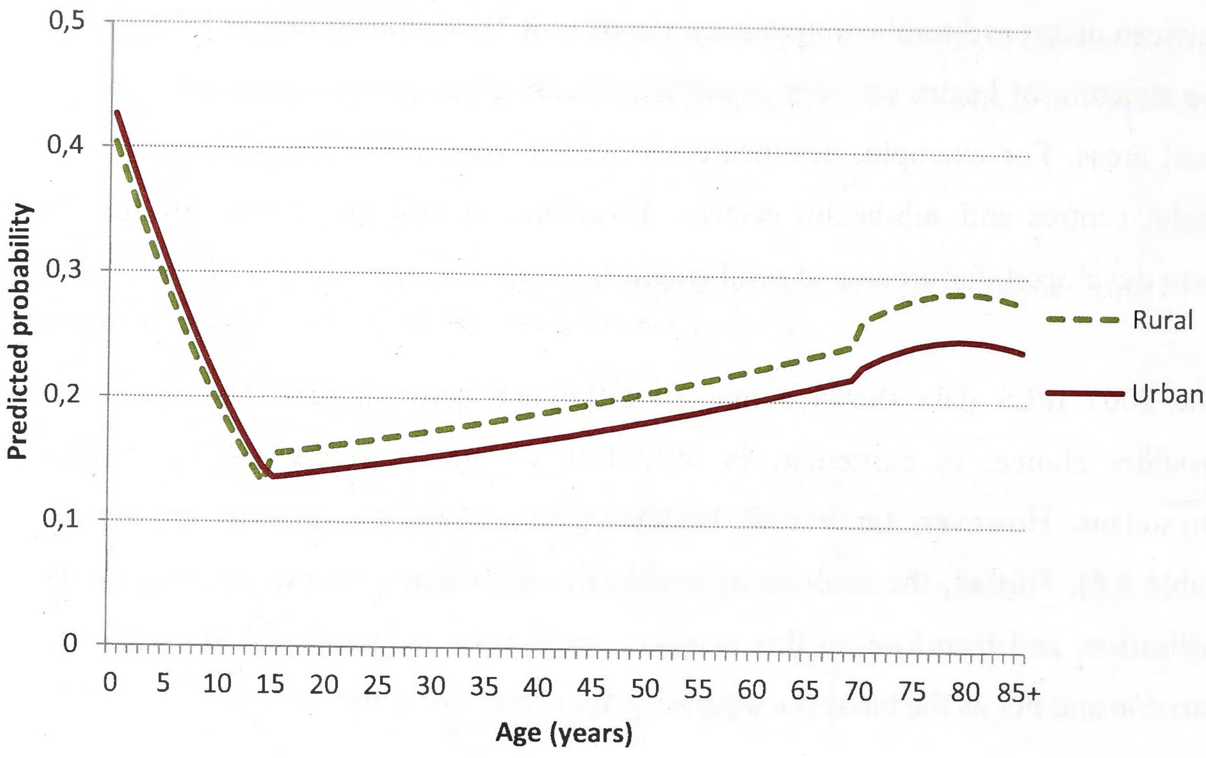
Table 4.6 Comparison of utilisation rate of healthcare providers by place of residence, 2007

	Healthcare utilisation rate (%), by region (%)		
	Urban	Rural	Total
Children utilisation rate	31.4	25.5	28.7
Adult utilisation rate	17.8	17.2	17.5
Elderly utilisation rate	27.5	25.0	26.1
Adult provider choice:			
Public hospital	6.3	3.1	4.8
Health centre	28.7	25.2	27
Private hospitals	4.8	1.7	3.3
Clinic	7.9	3.4	5.7
Physician	25.8	15.6	20.9
Paramedic	17.2	39.6	28
Traditional practices	9.3	11.4	10.3

Source: Calculated from 2007 IFLS for adult sample (15 years of age and over)

Referring to the result of multivariate analysis in Table 4.2, healthcare utilisation in rural areas is lower among children (odds ratio 0.837, $p<0.01$), but higher among adults (odds ratio 1.172, $p<0.001$) and the elderly (odds ratio 1.259, $p=0.253$). In terms of marginal effects, utilisation in rural areas is 3.1 percentage points lower ($p<0.01$) among children, but 2.1 percentage points higher ($p<0.01$) among adults. The effect of place of residence along the age of the respondents can be observed in Figure 4.10.

Figure 4.10 Mean predicted probability of healthcare utilisation among children, adults and the elderly by age



The result seems surprising and contradicts the common assumptions that rural residents are left behind in utilisation of healthcare. Some explanations emerge when the extent and the effects of social and economic characteristics of urban and rural populations are compared. These social and economic characteristic differences mask the high utilisation rate in rural areas.

Three variables that could affect this difference are education, insurance subscription and household income, all of which affect utilisation significantly. For all these three indicators, urban residences surpass their counterparts in rural areas (see Table 4.7). Due to their positive association with healthcare utilisation, these characteristics drive higher utilisation in urban areas. However, once these variables are manipulated in the model to be at the same level in both rural and urban areas, the utilisation among adults residing in rural areas increases.

Table 4.7 The marginal effect and the distribution of education, insurance and household income by region (urban/rural)

	Mean AME	Distribution of population	
		Urban (%)	Rural (%)
Education level			
No education	Ref	4.0	9.8
Primary	0.038**	28.9	48.1
Secondary	0.037**	54.5	38.0
Tertiary	0.044**	12.6	8.5
Health Insurance subscription		29.7	21.0
No insurance	Ref	70.3	79.0
Askes	0.066 ***	9.7	3.8
Private	0.052***	9.2	3.2
Askeskin	0.037***	10.4	14.0
Household income (Rp million)	0.0041**	2.5	1.7

On the effect of insurance subscription, insurance actually consists of three types of insurance: Askes, Private and Askeskin (see Chapter 4, Section B.2 for detail differentiation). When the insurance subscription is broken down into three types of insurance, and a similar logistic regression is conducted, the results indicate that the effect of Askes is the highest, followed by Private and Askeskin. The effect of utilisation in urban areas is thus greater because more urban residents are subscribed into Askes and Private insurance than are residents in rural areas. The effects of these variables and other influential variables serve to mask the high utilisation of healthcare in rural areas.

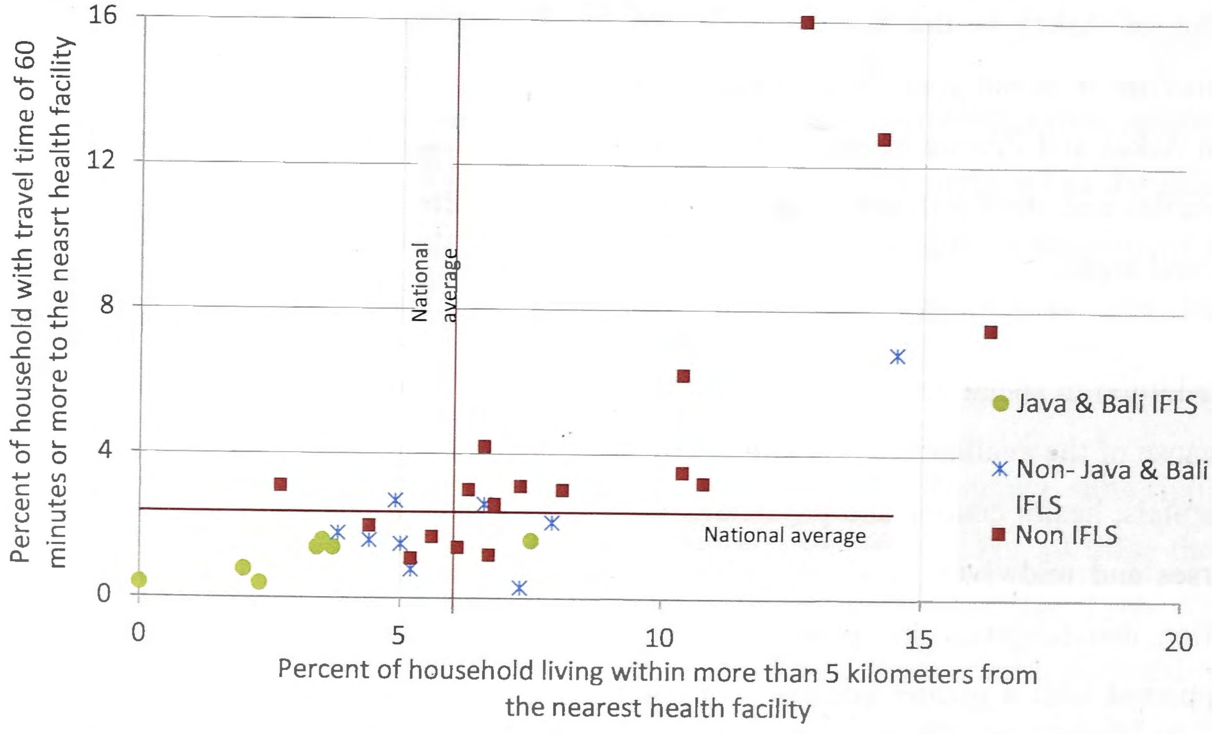
In addition to social economy factors, the utilisation of healthcare in rural areas is high because of the availability of a large number of nurses and midwives. In the absence of hospitals, health centres and physicians in their neighbourhoods, rural residents choose nurses and midwives. However, when we consider the quality of services, with the notion that hospitals and physicians generally can deliver better quality of services supported with a greater adequacy of equipment, then the access of rural residents to high-quality care is lower.

C.4.4. Island of Residence

The variable of island of residence represents an unobserved variable characterising overall development in the health system. It differentiates social economic condition, and the accessibility and quality of providers between Java/Bali from other islands (in this case, Sumatera, Nusa Tenggara, Kalimantan and Sulawesi). The distinction is important in assessing the advantages of living in regions with better access to high-quality healthcare.

Figure 4.12 shows accessibility in terms of travel time and distance to health facilities for the provinces included in the 2007 IFLS, as well as for other provinces not included in the IFLS (all of which are outside Java/Bali, with the exception of Banten province). Generally, geographical accessibility to health facilities in the IFLS provinces in Java/Bali is better than for the IFLS provinces outside Java/Bali and the non-IFLS provinces.

Figure 4.11 Travel time and distance of health facility from household dwelling, 2007



Data source: Plotted from 2007 Riskesdas

It is important to note that not all Javanese people live in Java. According to 2007 IFLS, 18.4% of Javanese live outside Java. The inclusion of the dummy variable of Java/Bali therefore serves two purposes: to isolate the effects of ethnicity from place of residence, and to indicate the role of accessibility and quality of healthcare providers. More details of the roles of accessibility and quality of healthcare provider in the likelihood of visiting healthcare providers are given using a more complex model in Chapter 6.

The result from the model in this study shows that being Javanese does not increase one's utilisation of healthcare (change in odds 6.3% at p-value = 0.623). Living in Java/Bali, on the other hand, has an odds ratio of healthcare utilisation among children of 49.5% ($P<0.001$) and among adults of 15.0% ($P<0.01$). In addition, the effect of island of residence remains strong both for Javanese and non-Javanese people, and therefore is an indication of higher utilisation among Java/Bali residents regardless of their ethnicity.

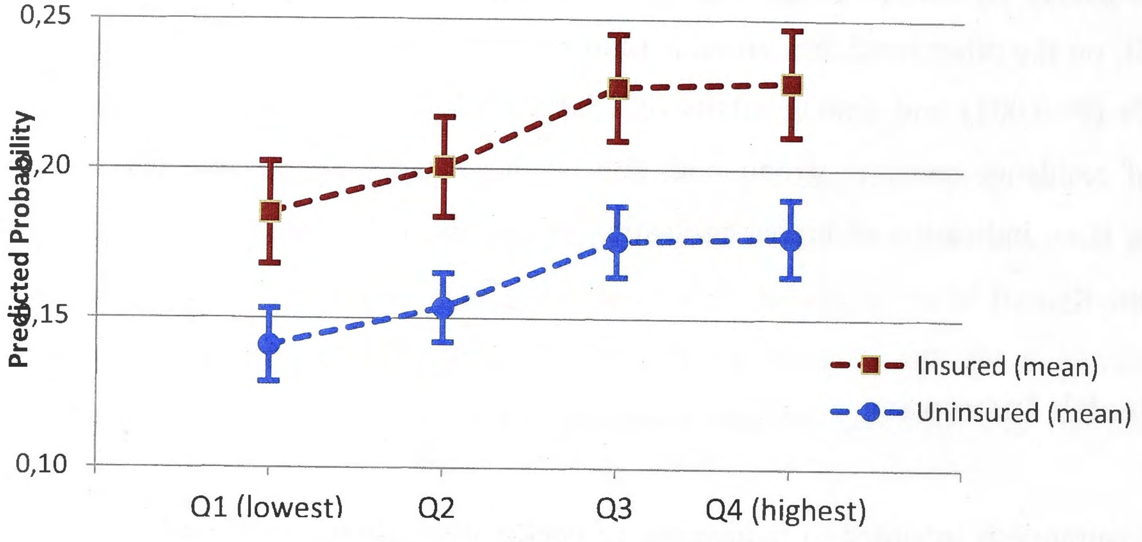
C.5. Health Insurance

Health insurance is intended to reduce out of pocket expenditure and financial barriers to accessing medical care, especially for the poor (Feldstein, 2011, Zweifel and Manning, 2000). Insurance subscription is expected to have a positive association with healthcare utilisation. This effect was found in previous studies in Indonesia (Hidayat et al., 2004, Rokx et al., 2010, Sparrow et al., 2010) and elsewhere among children (Cassedy et al., 2008, Newacheck et al., 1998, Rosenbach et al., 1999, Sills et al., 2007, Wolfe, 1980), adults and the elderly (Cheng, 2003, Cheng and Chiang, 1997, Holly et al., 1998, Kwon, 2009, Newhouse, 1993).

In this study, the insurance variable is not included in the Children model, since the information is not available in the IFLS survey data. Therefore, this discussion will apply only for adults and the elderly. Among adults, as expected, insurance subscription has a positive association with healthcare utilisation. The odds ratio of utilisation for an insured person is on average 43% higher ($p<0.001$) than for an uninsured person. In terms of substantive significance, the standardised coefficient of insurance effect is 0.08, which is close to significant. Among the elderly, the magnitude of the effect is similar, but is not statistically significant.

Health insurance subscription increases the probability of healthcare utilisation at all levels of household income, and the gap in utilisation between uninsured and insured is similar across income quartiles. In other words, the effect of insurance subscription is significant, and does not vary by income.

Figure 4.12 Predicted probabilities of insurance subscription effects by income quartile, with 95% confidence interval



Several schemes of health insurance exist in Indonesia, including mandatory health insurance for civil servants (Askes), military forces (Asabri) and private employees (Jamsostek) and social health insurance for the poor (Askeskin), as well as various commercial insurances. Each of these insurances has its own specific targets and preferred providers. For example, Askes and Askeskin are valid in most public healthcare providers and only a small proportion of private healthcare providers, while commercial insurance is mostly valid at private providers. Jamkesmas is only intended for poor and near-poor groups, while commercial insurances generally serve higher-income groups. Therefore, it is not surprising that the average effect of insurances (a combination of all insurance categories) is similar across income groups.

However if we go into detail by examining effects of each type of insurance to choice of providers, we may notice the variability in their effects to healthcare utilisation. Hidayat et al. (2004) shows that Askes has a strong positive effect on access to public outpatient care, while Jamsostek has a positive effect on both public and private care utilisation, with the strongest effects found among the poor. Chapter 5 examines further the effects of health insurance on the choice of providers.

C.6. Health Needs

Previous studies have reported a strong association between perceived health status and healthcare utilisation for outpatients (Cafferata and Kasper, 1985, Fan et al., 2011, Foreman et al., 1998, Yu et al., 2009) among children (Janicke et al., 2001, Newacheck and Halfon, 1986, Palacio-Vieira et al., 2012), adults and the elderly (Da La Hoz and Leon, 1996, Haug, 1981, Wolinsky et al., 1988). Wolinsky (1978) found that in the US, most of the explained variances in healthcare utilisation are in fact because of illness-morbidity characteristics.

In all three models in this study (Children, Adult and Elderly), self-reported general health status (good or poor health) is included as a perceived health status variable. The logistic estimations (see Table 4.2) show that the effect of health status is significant among children and adults, but not for the elderly. The findings of the Adult model are consistent with a previous study conducted in the Indonesian context using 1997 IFLS data (Hidayat, 2008). However, general health status does not appear to be associated with utilisation among the elderly, although this may be controlled away by inclusion of chronic diseases. The diminishing effect of general health status among the elderly has also been found in previous studies among this cohort (Rosner et al., 1988, Wolinsky et al., 1988).

The model also estimates positive effects of severity of illness to utilisation, measured by the number of days staying in bed due to illness. People with severe illness are more likely to utilise healthcare in all models. Severity of illness reflects the intensity of sickness experienced by the respondents. This finding is consistent with previous studies in other countries, and with theories of health utilisation (Andersen, 1995, Berra et al., 2009, Rosenstock, 1966).

One evaluated health status variable is included in the model. The variable is indicating whether a person (age 40 and above) was diagnosed by a medical health professional with one or more types of chronic condition (hypertension, diabetes, heart attack, stroke or cancer). In the context of Indonesia, this is the first model to include evaluated health status in a demand for healthcare utilisation model. Results for the Elderly model show that having a chronic disease is positively associated with utilisation of healthcare (odds ratio 2.679 p-value <0.001) with a standardised coefficient of 0.24. Comparing by sex, the probability is significantly higher for females at 0.266 (95% CI 0.2367–0.2886) than for males at 0.1795 (95% CI 0.1548–0.2042).

Since information of professional diagnosis of chronic diseases is available not only for the elderly, but also for respondents aged 40 and above, it might be useful to assess whether similar effects also apply to all respondents aged 40 and above. For this purpose, a separate logistic regression model was developed using the adult/elderly sample aged 40 years and above. In this model, all dependent variables in the adult model were included and the chronic disease variable was introduced. The detailed results of the logistic estimation for this model are provided in Appendix 9.

The results show that chronic diseases are associated with increased healthcare utilisation (odd ratio 1.936, p-value<0.001). The standardised coefficient of chronic disease is 0.16, indicating the very strong influence of chronic disease on healthcare utilisation. However, the effect of chronic diseases among the elderly is stronger (standardised coefficient of 0.24) than for adults/elderly aged 40+, indicating that older people's decisions to utilise healthcare are more strongly affected by chronic diseases.

Adopting Heise's criteria of substantive significance using standardised coefficients of approaching 0.10 as the cut-off point (details of the standardised regression are presented in Appendix 5), it is found that health need variables are among the most significant variables substantively. Other substantively significant variables include age of children and the elderly, and sex of adults and the elderly.

Table 4.8 Estimated standardised coefficients of logistic regression for health need, age and sex

	Fully standardised coefficient		
	Children (<15 yrs)	**Adult (15–69 yrs)**	**Elderly (70+ yrs)**
Health need			
Self-rated health	0.09	0.12	0.03
Severity of illness	0.31	0.27	0.25
Chronic disease	-	-	0.24
Age	-0.24	0.05	-0.32
Sex	-0.03	0.13	0.16
Region of residence	-0.04	0.04	0.05

This shows that the magnitude of the effects of health need is relatively higher than for other predisposing (demographic) and enabling (social economics) variables. As indicated by Wolinsky (1978), this high association shows that health need is the immediate or closest causal factor of healthcare utilisation.

C.7. Carer's Characteristics

Identifying child healthcare needs is challenging because of the special characteristics of childhood-related healthcare development, dependency on parents/carers, distinctive disease epidemiology from adults and unique demographic characteristics (Forrest, 2004). In addition to children's predisposing, enabling and health needs factors, carer's characteristics become important in the examination of children's healthcare utilisation, as children rarely initiate seeking medical care by themselves.

Several studies have found that carer's[17] characteristics are a strong predictor of children's healthcare use. Janicke et al. (2001) shows that maternal perception of child health and maternal functioning influence the decision to seek healthcare on behalf of children. Child health status as perceived by parents is reported to be a major predictor of healthcare utilisation among children (Berra et al., 2006, Woodward et al., 1988). Other studies have indicated past patterns of maternal use of healthcare as a powerful predictor of amount of healthcare use by children (Riley et al., 1993, Starfield et al., 1985, Tessler and Mechanic, 1978). The roles of other parent demographic (age and sex) and social economic (education and employment) characteristics varied (Halim et al., 2011, Horwitz et al., 1985, Newacheck and Halfon, 1986, Pillai et al., 2003, Wolfe, 1980).

In this study, the demographic and social economic strata of carers are added to the Children model. This includes parents' age, sex, education and employment status. Parents' records on past healthcare-seeking behaviour variables are not available in the IFLS survey. The logistic regression estimates (see Table 4.2) show that parents' age, sex and employment status are not significant predictors of children's use of healthcare. Parents' education level, on the other hand, has a positive association with healthcare

[17] In this study, carer's (not parent's) characteristics are used as the independent variables acknowledging that there are children who do not live with their parents, although almost all carers in the sample of this study are parents.

use by their children. In terms of substantive significance, the standardised coefficient for parents' education is 0.03, meaning that an increase of one standard deviation in level of education only increases the odds of utilisation by 0.03 standard deviation. Thus, the effect of parents' education is not as high as other factors, such as children's age (standardised coefficient 0.24), severity of illness (standardised coefficient 0.31) or other characteristics.

D. Summary

This chapter analysed the determinants of healthcare utilisation using the 2007 IFLS. It sought to understand how healthcare utilisation is shaped by demographic, social economic and health need factors. In doing so, it also provided additional knowledge on the non-monotonic effects of age on utilisation by employing separate models for children, adults and the elderly. It also analysed the effects of chronic disease, which reflects the role of evaluated health need, which is rarely addressed in studies of healthcare utilisation in Indonesia.

The analysis revealed that the factors influencing healthcare utilisation during the life course of the Indonesian population are quite distinctive. The utilisation of healthcare across age shows a decrease among children, an increase among adults, and a decrease among the elderly. Generally, female's utilisation is higher (except during childhood) and is more responsive to changes in social economic conditions. Most of the demographic characteristics investigated here are influential on healthcare utilisation among adults, but not among children and the elderly. Parent's and social economic variables have a role in shaping utilisation among children, while only income and health need are influential among the elderly.

From a public policy perspective, this chapter indicates that, in general, there is equitable access to healthcare across genders, ethnicities, religions, income levels and places of residence. However, inequity can be seen by observing the differential in utilisation between populations living in or outside of Java/Bali, as well as between groups with different levels of education. This inequity of access may be more visible if quality of service is taken into account, and if findings were inclusive of those populations living in less-developed areas not covered in the 2007 IFLS survey (that is, in those provinces in the eastern part Indonesia).

Determinant analysis in healthcare utilisation is able to show the extent to which demographic, non-demographic and health need factors influence healthcare utilisation. However, many questions remain. For example, what influences people in choosing healthcare providers? How do groups of population differ in their choice of provider? What is the role of social health insurance in Indonesia? The next chapter examines the determinants of choice of provider in Indonesia, while also attempting explanations of above-unanswered questions.

Chapter 5
Determinants of Choice of Providers

When a person is sick, the immediate choice is whether to seek medical care. This simplified binary option is described and examined in the previous chapter. Once it has been decided to seek care, the person faces various choices of healthcare provider. Thus, to analyse this decision-making process, a two-step model is adopted. This model holds that the decision to seek care and the decision to choose a provider are not simultaneous, but are two separate processes.

This chapter is devoted to investigating choice of provider and the determinants for outpatient care utilisation in Indonesia, including seeking an explanation for differentials in the choice of provider among groups of population. This analysis extends the identification of healthcare utilisation determinants as outlaid in Chapter 4.

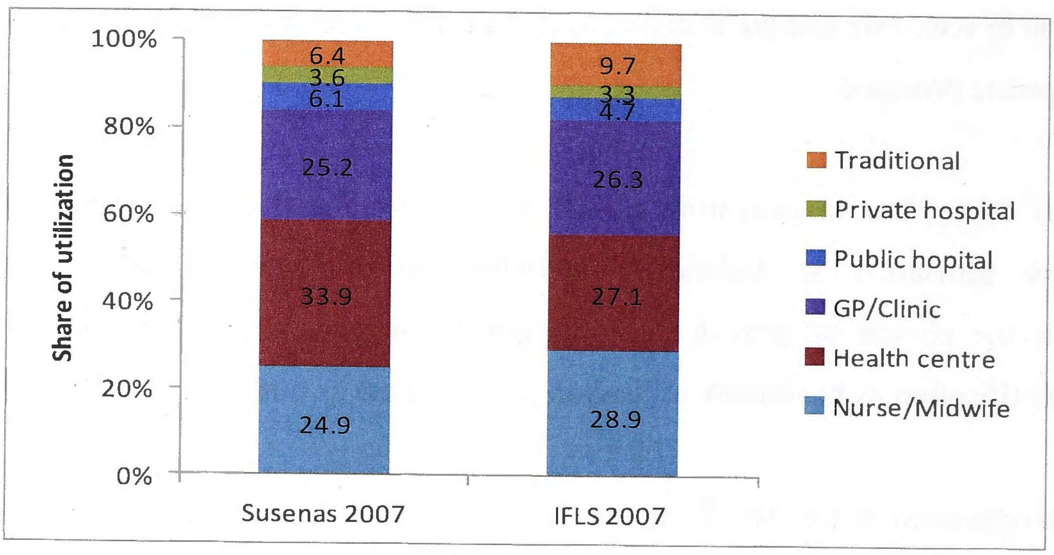
This chapter is organised as follows. First, the extent of choice of provider in outpatient care utilisation in Indonesia is presented. Second, the model development as a tool to examine the determinants is described. Since the basis of the theoretical framework for the analysis is similar to that for healthcare utilisation (see Chapter 4, Section B), the model development is described in a more compact manner. Finally, the role of provider characteristics in the choice of provider is discussed.

A. Choice of Providers in Indonesia

There are various healthcare providers in Indonesia to choose from when seeking healthcare. The categories of provider are traditional healthcare providers, health centres, auxiliary health centres, hospitals, clinics, physician practices (specialists and GPs) and individual practice of nurses and midwives. Providers can also be categorised based on ownership into public and private providers. Public providers include public hospitals, health centres and auxiliary health centres. The rest are privately owned.

2007 IFLS data shows that the majority of people choose health centres when seeking healthcare, followed by paramedics, nurses and midwives, and then GPs/clinics. Public and private hospitals are the two providers least visited. 2007 Susenas data, which is more representative in terms of sample coverage of the Indonesian population, show a similar trend in the choice of provider (see Figure 5.1). Although the 2007 IFLS data cover a smaller sample and number of provinces, on the choice of provider, it is consistent with the much larger 2007 Susenas survey.

Figure 5.1 Choice of providers for outpatient care in Indonesia according to 2007 Susenas and 2007 IFLS

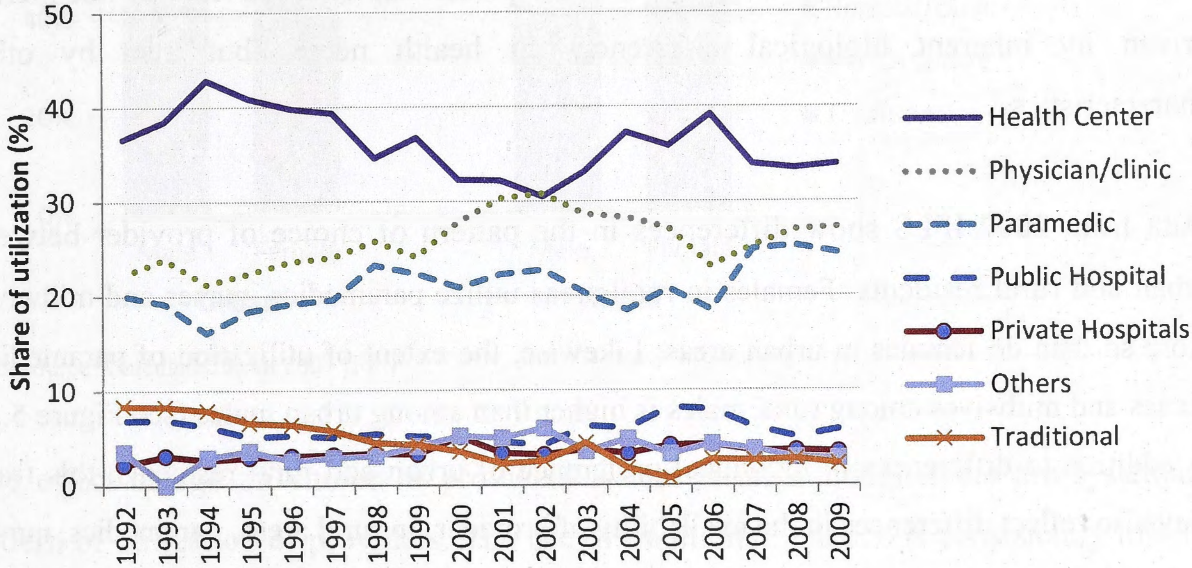


Data source: Calculated from 2007 Susenas and 2007 IFLS

Health centres, paramedic, nurse and midwife practices, and physician practices are the main providers of outpatient care in Indonesia. This can be explained partly by the fact that these providers are the geographically most accessible providers. Hospitals, both private and public, are rare in non-urban areas and are formally intended for referral services. It is not surprising that hospitals are rarely visited by people for outpatient purposes. Traditional practices are also available. However, their usage is relatively limited, probably due to the lower perceived quality of care provided.

The domination of health centres, GPs/clinics and paramedics, nurses and midwives in outpatient service use has remained steady since the early national surveys in the 1990s. However, the use of health centres declined between 1994 and 2003, before increasing again recently. The use of physicians, clinics and paramedics nurses and midwives on the other hand, fluctuates in the opposite direction to health centres, suggesting a possible substitution between these two types of provider. Public intervention may have played an important role in the shifting of healthcare service preferences among users (Rokx et al., 2010). The use of other providers has been relatively steady and has never risen above 10% of total utilisation. The use of traditional practices also has been slightly declining since 1992 (see Figure 5.2).

Figure 5.2 Trends in share of utilisation of healthcare providers, Indonesia 1992–2009



Data source: Calculated form 1992–2009 Susenas

Demographic characteristics have been identified to affect healthcare utilisation as described in Chapter 4. The effects of sex do not end with the decision to seek medical care. Previous studies have shown that sex is significantly associated with the preference of certain types of healthcare provider (Hidayat and Pokhrel, 2009, Prentice, 2006). In this study, there is a strong indication that sex also plays an important role in the decision to choose a healthcare provider (see Table 5.1).

Table 5.1 Share of outpatient care utilisation by type of healthcare provider in Indonesia, 2007

Providers	Male	Share to total utilisation (%)			
		Including prenatal visit		Excluding prenatal visit	
		Female	Total	Female	Total
Traditional	12.8	8.2	9.7	8.4	9.9
Health centre	22.8	29.4	27.1	30.1	27.5
Hospital/clinic	17.2	11.5	13.4	11.6	13.6
Physician	26.0	18.1	20.8	18.6	21.3
Paramedic/nurse/midwife	21.2	32.9	28.9	31.3	27.8
Total share	100.0	100.0	100.0	100.0	100.0

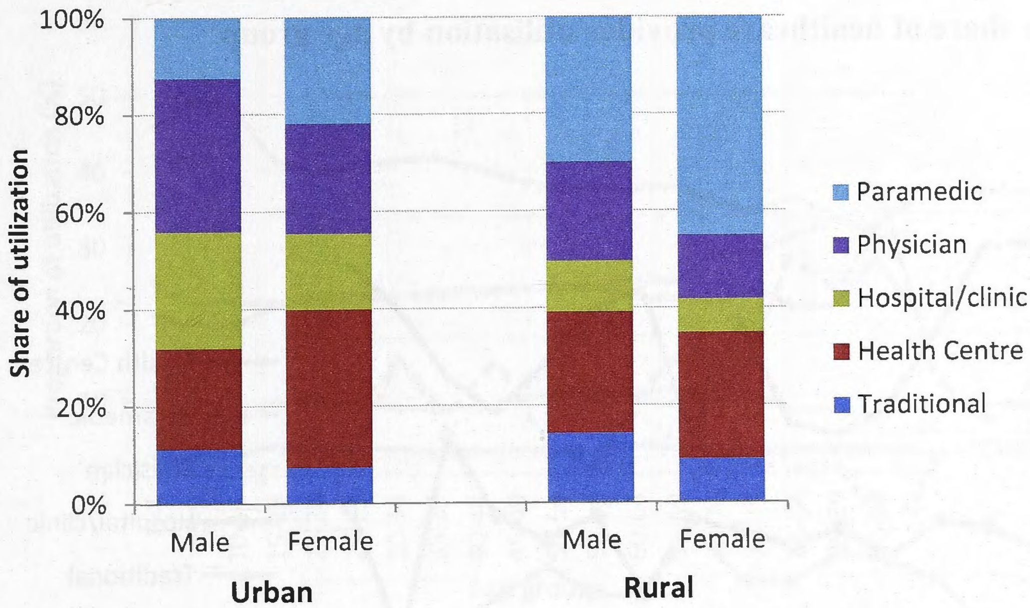
Data source: Calculated from 2007 IFLS

Among males, the use of physicians is more prevalent. Among females, the use of paramedics, nurses and midwives is significantly higher as compared to preferences for other providers. The high utilisation of paramedics, nurses and midwives may be attributable to prenatal care and maternal-related health consultations. However, when utilisation for prenatal purposes is excluded, the dominant use of paramedics and health centres remains evident. This suggests that the preference to a provider is not merely driven by inherent biological differences in health needs, but also by other characteristics.

Data from 2007 IFLS show differences in the pattern of choice of provider between urban and rural residents. Females in rural areas utilize paramedics, nurses and midwives more so than do females in urban areas. Likewise, the extent of utilization of paramedics, nurses and midwives among rural males is higher than among urban males (see Figure 5.3). In addition to differences in individual preference of urban and rural residents, this trend may also reflect differences in the availability of provider. In rural areas, paramedics, nurses and midwives are generally more accessible geographically than other providers. Study by Erlyana (2011) using 2000 IFLS data indicated that urban dwellers are not sensitive to distance. Rural dwellers, in contrast, are sensitive to travel distance. As distance is perceived as barriers, rural dwellers tend to choose paramedics, nurses and midwives which are closer than other provider to their home.

In this chapter, the discussion focuses on the role of user's characteristics on choice of provider. The roles of distance, as one of indications of health care availability, other provider's characteristics and how they interact with user's characteristic will be investigated using random parameter logit model and it's estimated results are presented in Chapter 6. However, recognizing that choice of provider can be confounded by differences in the availability of supply, multinomial logit model of choice of provider in this chapter requires the inclusion of place of residence (i.e. urban or rural) as covariates.

Figure 5.3 Share of choice of providers among males and females residing in urban and rural areas



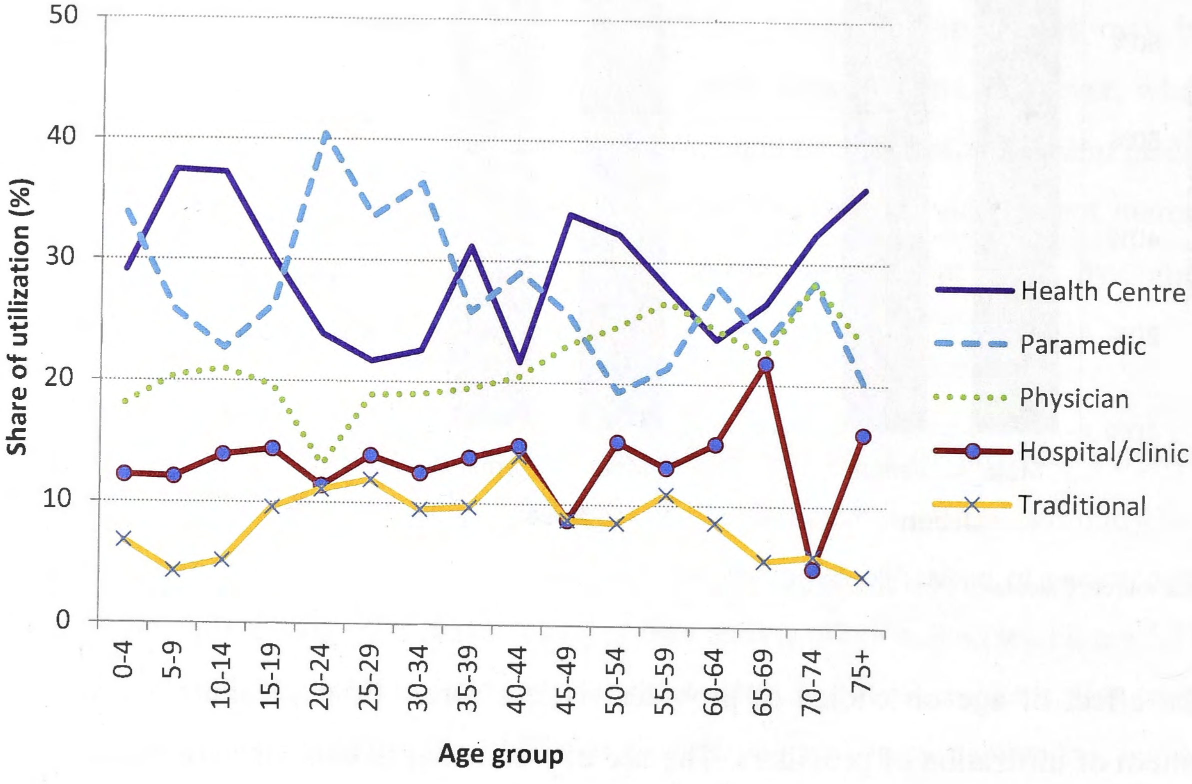
Data source: Calculated from 2007 IFLS

The effect of age on choice of providers is less clear, although there are systematic pattern of utilization of providers. The use of traditional practice is consistently low for all ages. Likewise, the use of hospitals and clinics is low, but with a tendency to increase in popularity in later life. Among children, the use of physicians is about 20%. As they get older, their likelihood of utilising a hospital increases. The two types of provider used most often across the population groups at any age are health centres and paramedics, nurses and midwives. However, the fluctuation along age is quite visible (see Figure 5.4). Using only bivariate analysis may not be sufficient to examine the preferences towards providers by age, as these are probably affected by other factors.

The small sample used is one possible explanation for the peaks and throughs in the patterns found of utilisation of health centres and paramedics, nurses and midwives by age group, as well as the fluctuation of hospital utilisation as the population ages. Thus, the consistency of the IFLS trend on choice of provider can be compared with the 2007 Susenas, which boasts national coverage including all provinces included in the IFLS, but with a much higher number of samples representing all districts.[18]

[18] Province represents the highest administrative level below the national level, and these are then divided further into districts. 2007 Susenas was conducted in all provinces and all districts. Samples for healthcare utilisation were selected using multi-stage random sampling and are representative up to the district level. 2007 IFLS sampling is also based on multi-stage random sampling, but it does not cover all districts in the selected provinces. Consequently, the number

Figure 5.4 The share of healthcare provider utilisation by age group



Data source: Calculated from 2007 IFLS

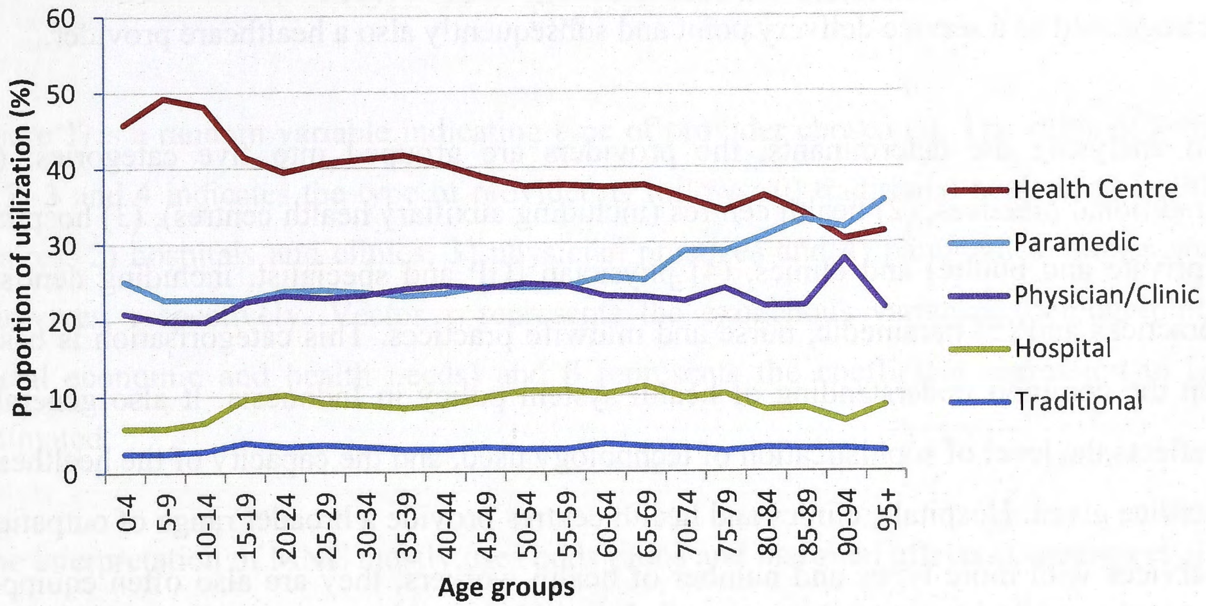
The 2007 Susenas produces smoother trends along the ages of respondents, with only minor fluctuations in later life. Overall, however, the trend of choice of provider is consistent with 2007 IFLS.[19] The use of traditional healers and hospitals is consistently low, while the use of physicians and clinics is relatively stable. The use of paramedics, nurses and midwives increases with age, and the use of health centres decreases with age.

---

of samples in Susenas is much higher than in IFLS. This graph is built from 145,651 individuals, while IFLS uses 5,180 individuals.

[19] There is a difference in the categorisation of providers. In 2007 Susenas, clinics are pooled together into one category with physicians; while in 2007 IFLS, clinics are in one category with hospitals. The resulting categorisation is a consequence of different questions between the two surveys. However, the results are similar.

Figure 5.5 The proportion of healthcare provider utilisation by age group according to the 2007 Susenas, in provinces included in the 2007 IFLS



Data source: Calculated from 2007 Susenas

B. Model Development

Unlike in previous chapters in which the samples were separated into three models based on age (Children, Adult and Elderly models), in this chapter the main model is for the adult sample aged 15 and above (including the elderly, and called 'the model'. Determinant analysis in this chapter uses data from the 2007 IFLS. Due to the small sample size for age 70+, no specific model is developed for the elderly, to avoid high standard error caused by more choices in the dependent variables. Further, there would be no systematic difference in the trend of provider choice for the elderly as compared to the adult model.

The term 'healthcare provider' in this chapter refers to the service delivery points at which medical care services are provided to outpatients by any type of available health worker. In health centres, hospitals[20] and clinics, healthcare services can be delivered by physicians, nurses or midwives working in that facility. In this case, healthcare providers refer to health centres, hospitals and clinics, and do not refer to individual

[20] Although administratively a hospital is a referral service, in practice both public and private hospitals provide outpatient services without prior referral from lower strata providers; that is, health centres or private practitioners.

health workers. On the other hand, GPs, physicians, dentist, nurses and midwives often also work individually, independent from a healthcare facility. In this case, they are categorised as a service delivery point and subsequently also a healthcare provider.

In analysing the determinants, the providers are grouped into five categories: (1) traditional practices, (2) health centres (including auxiliary health centres), (3) hospitals (private and public) and clinics, (4) physician (GP and specialist, including dentists) practices and (5) paramedic, nurse and midwife practices. This categorisation is based on the common understanding of health system policy in Indonesia. It also generally reflects the level of sophistication of technology used, and the capacity of the healthcare service given. Hospitals, clinics and health centres provide a broader range of outpatient services with more types and number of health workers; they are also often equipped with advanced medical equipment. Private physicians and paramedic, nurse and midwife practices provide service individually and are usually less well equipped with medical tools.

Although in practice a person can choose to self-care, in this model self-care is excluded as a possible option. One reason is that the focus is on the choice of care offered by healthcare providers and that this thus does not include self-care. Another reason is that, in the 2007 IFLS questionnaire design, it is not possible to pick self-care as a mutually exclusive option of care, so that including it in the multinomial logit model would require a complex combination of options that would make interpretation difficult.

Multinomial logistic regression (MNL) will be used in this chapter to estimate the effect of various demographic, social economic and health need factors on the choice of providers. MNL is used largely because it represents the natural decision problem faced by people when choosing a provider (Scott and Freese, 2006). This model has also been used in previous studies on the demand for healthcare with multiple choices of provider, in both Indonesia and elsewhere (Akin et al., 1986, Dong et al., 2008, Grobler and Stuart, 2007, Hidayat and Pokhrel, 2009, Lawson, 2004, Mwabu et al., 1993, Yip et al., 1998).

MNP for choice of provider in Indonesia is expressed in a probability equation. The probability that an individual I will choose alternative j is given by equation:

$$\Pr(y_i = j) = \frac{e^{\beta_j x_i}}{\sum_{k=0}^{4} e^{\beta_k x_i}}, \text{for } j = 0,1,\ldots,4 \quad (5.1)$$

where Y_i is a random variable indicating type of provider chosen (j). The value of j =0, 1, 2, 3 and 4 indicates the type of provider as follows: 0) traditional healers, 1) health centres, 2) hospitals and clinics, 3) physician practices and 4) paramedics, nurses and midwives, respectively. Vector x_i represents the exogenous variables (demographic, social economic and health needs) and β represents the coefficient regression to be estimated.

The interpretation of MNL mostly uses odds ratios and marginal effects (Cameron et al., 1988). Odds ratios compare the probability of choosing a certain type of provider to a base category:

$$\Pr(y_i = j | y_i = j \; or \; 1) = \frac{\Pr(y_i = j)}{Pr(y_i = j) + \Pr(y_i = 1)} = \frac{e^{\beta_j x_i}}{1 + e^{\beta_j x_i}}, \text{for } j = 0,1,\ldots,4$$

The marginal effect is also used to evaluate the relative change in the probability of choosing a certain type of provider as a response to a one-unit change in an independent variable:

$$\frac{\delta p_{ij}}{\delta x_i} = p_{ij}(\beta_i - \bar{\beta}_j)$$

where $\bar{\beta}_j = \sum_i p_{ij}\beta_i$ is a probability weighted average of theβ_i. The marginal effect is calculated at all points and the average is taken as the AME.

MNL is subject to the IIA assumption (McFadden, 1986), which assumes that the probability of an alternative being chosen is independent of other alternatives. This property is not particularly appealing in consumer behaviour studies (Greene and Zhang, 2003). To test the IIA assumption, a Hausman specification test and a Small-Hsiao IIA test was conducted (Cameron et al., 1988, Scott and Freese, 2006).

The model is built upon the behavioural model of service use (Andersen, 1995), which also provided the analytical framework in the healthcare utilisation determinant analysis in Chapter 4 and has been described in the theoretical framework in Chapter 3. With this framework, the independent variables are similar to those used for determining healthcare utilisation, consisting of three main factors of health service use: predisposing, enabling and need factors (see Figure 2.1).

Differences in the pattern of choice of provider between rural and urban may not be completely attributable to differences in the characteristic of demographic, social economic and health need of urban and rural dwellers. As the choice of certain types of health provider are confounded by geographical, distance and other characteristics which are also specific to urban and rural environment, it is important to introduce place of residence (urban or rural) as a covariate in the model.

Table 5.2 Description of the variables used in the MNL regression

Variable	Description	Mean	SD
Choice of provider			
	Traditional	0.10	0.30
	Health centre	0.27	0.44
	Hospital/clinic	0.13	0.34
	Physician	0.21	0.41
	Paramedic/nurse/midwife	0.29	0.45
Demographics			
Age	Age in years (min 15, max 90)	41.47	16.92
Sex	1 if female, 0 male	0.66	0.47
Marital Status	1 if currently married, 0 single/widowed/divorced	0.74	0.44
Householder status	1 if the head householder, 0 otherwise	0.35	0.48
Religion	1 if Islam, 0 otherwise	0.89	0.32
Ethnicity	1 if Javanese, 0 otherwise	0.43	0.49
Household Size	The number member in the household (1, 2, 3, …, 15+)	6.66	3.06
Social economic			
Education	Highest education level attended; 0=no schooling 1=primary 2=secondary 3=tertiary and higher	1.51	0.78
Facility knowledge	Number of health facility locations known by the respondent (0,1, … , 10+)	5.78	1.81
Health insurance subscription			
	Not insured	0.68	0.47
	Askes	0.10	0.30
	Askeskin	0.14	0.35
	Private insurance	0.07	0.26
Income	Million rupiah per month (min 0.086, max 32.8)	0.68	0.47
Place of residence	1 if rural, 0 urban	0.48	0.50
Island of residence	1 if Java or Bali island, 0 otherwise	0.63	0.48
Health needs			
Self-rated health	1 if health condition is poor, 0 good	0.33	0.47
Severity of illness	1 if at least 1 day staying in bed due to illness in the last 4 weeks, 0 none	0.66	0.48
Number of sample (N)		2,895	

C. Factors Affecting Choice of Providers

A MNL model[21] is used to examine factors associated with the choice of healthcare provider. The dependent variable is a set of five choices of healthcare provider: traditional practice (serving as the base reference), health centre, hospital, physician or paramedic, nurse and midwife practices. The independent variables include demographic, social economic and geographic characteristics, which can be categorised as predisposing, enabling and need factors according to Andersen's health service use framework (Aday and Andersen, 1974, Andersen, 1995). Table 5.3 shows the results of the MNL model estimation of choice of provider using the 2007 IFLS data.

Table 5.3 Estimation of healthcare provider choice*

	Health centre		Hospital and clinic		Physician		Paramedic, nurse, midwife	
Variable	Coef.	S.E.	Coef	S.E.	Coef	S.E.	Coef	S.E.
Age	-0.075‡	0.006	-0.074†	0.032	-0.036	0.029	-0.104‡	0.028
Squared age	0.001‡	0.000	0.001‡	0.000	0.001*	0.000	0.001‡	0.000
Sex	0.854‡	0.182	0.119	0.206	0.219	0.186	1.004‡	0.185
Marital status	0.680‡	0.161	0.106	0.184	0.100	0.166	0.672‡	0.165
Householder status	0.176	0.211	0.229	0.242	0.323	0.217	0.332	0.213
Household size	0.075‡	0.029	0.029	0.033	-0.010	0.030	0.036	0.029
Religion	-0.483*	0.272	-0.551*	0.299	-0.765‡	0.273	-0.507*	0.271
Ethnicity	0.168	0.167	0.240	0.190	0.490	0.171	0.500‡	0.166
Education	-0.042	0.122	0.381‡	0.137	0.203*	0.125	-0.122	0.123
Index of facility knowledge	-0.174‡	0.045	-0.030	0.051	-0.015	0.046	-0.053	0.045
Health insurance								
Askes	0.346	0.257	0.704‡	0.269	-0.136	0.261	-1.004‡	0.310
Askeskin	0.896‡	0.225	0.453	0.281	0.105	0.251	0.075	0.234
Private	-0.687*	0.367	1.725‡	0.298	0.377	0.306	-0.563*	0.333
Region of residence	-0.446‡	0.157	-0.680‡	0.183	-0.566‡	0.163	0.478‡	0.158
Island of residence	0.414†	0.166	0.534‡	0.194	0.515‡	0.175	0.119	0.165
General health status	0.083	0.169	0.580‡	0.188	0.403†	0.172	0.150	0.168
Severity of illness	0.283*	0.151	0.353†	0.175	0.566‡	0.159	0.410‡	0.151
Income	-0.125‡	0.034	0.016	0.029	0.035	0.027	-0.064†	0.031
Constant	0.825	0.565	-1.713‡	0.640	-0.677	0.579	0.121	0.572

Note: *traditional practice is set as the base referral. ‡, † and * represent significance at the 1%, 5% and 10% levels, respectively.

---

[21] The MNL model requires that the model pass the IIA assumption. A Small-Hsiao IIA test is conducted for the model and the results show that the model does not violate the IIA assumption.

The estimates show that all demographic (with the exception of householder status), social economic and geographic variables had a significant association with at least one choice of provider. However, comparing the effects of each variable is more complex, as all estimates are relative to the reference category. Moreover, the estimates are calculated at the mean of sample value, and therefore may not reflect the effects across sample variability and are not the average effect of these variables (Cameron et al., 1988).

To ease the interpretation, the estimates can be transformed into the marginal effect, which is calculated as the average of the effects at all sample points. Table 5.4 shows the estimates of average marginal effects (AME) of the same MNL model. AME represents the average change of probability of choosing a particular healthcare provider in response to a one-unit change of an independent variable. For binary variables such as sex, a one-unit change in independent variable means a discrete change from 0 (male) to 1 (female). Different from the coefficient of estimates in Table 5.3, which are calculated at one point (the sample mean), AME is the average of effects from all sample points, and therefore reveals the overall effect of the independent variables.

Estimates of AME in Table 5.4 reflect the overall associations between demographic, social economic and health needs and choice of healthcare provider. These effects are less pronounced on traditional practice, as shown by the fewer variables with significant AMEs. The variables with significant effects are sex, severity of illness and religion. Muslims are more likely to visit traditional practices and are less likely to visit physicians as compared to non-Muslims, although this effect is small. Females are less likely to choose traditional practices. A person with a more severe illness is also less likely to choose a traditional practice. The limited association between demographic, social structure, economic and health needs and choice of traditional practices indicates the strong influence of beliefs and cultural values on traditional practices (Wiseman et al., 2008).

Table 5.4 Estimate of the average marginal effect of the MNL model

Variables	Traditional		Health centre		Hospital and clinic		Physician		Paramedic, nurse, midwife	
	AME	SE	AME	SE	AME	SE	AME	SE	AME	SE
Age	-0.001	0.000	0.000	0.001	0.001†	0.001	0.002‡	0.001	-0.003‡	0.001
Squared age										
Sex	-0.053‡	0.014	0.049†	0.022	-0.043‡	0.015	-0.059‡	0.019	0.106‡	0.022
Marital status	-0.033	0.012	0.022	0.019	-0.022	0.014	-0.044	0.017	0.078‡	0.019
Household status	-0.023	0.016	-0.019	0.024	-0.001	0.018	0.018	0.022	0.025	0.024
Household size	-0.003	0.002	0.011‡	0.003	0.000	0.002	-0.008‡	0.003	0.000	0.003
Religion	0.049†	0.022	0.006	0.028	-0.003	0.020	-0.050†	0.024	-0.002	0.027
Ethnicity	-0.031	0.013	-0.040†	0.018	-0.010	0.014	0.035†	0.017	0.046†	0.018
Education	-0.005	0.009	-0.021	0.014	0.036‡	0.010	0.027†	0.012	-0.038‡	0.014
Index of facility knowledge	0.007*	0.003	-0.026‡	0.005	0.004	0.004	0.010†	0.005	0.005	0.005
Health Insurance:										
Askes	0.013	0.020	0.125‡	0.031	0.091‡	0.018	-0.015	0.026	-0.214‡	0.041
Askeskin	-0.033*	0.018	0.140‡	0.021	0.014	0.021	-0.050†	0.025	-0.071‡	0.023
Private	0.003	0.024	-0.155‡	0.050	0.198‡	0.018	0.061†	0.030	-0.108†	0.043
Region of residence	0.018	0.012	-0.068‡	0.017	-0.048‡	0.014	-0.065‡	0.016	0.162‡	0.017
Island of residence	-0.031†	0.013	0.024	0.019	0.021	0.015	0.034*	0.018	-0.049‡	0.019
General health status	-0.022*	0.013	-0.035*	0.018	0.039‡	0.013	0.031*	0.016	-0.014	0.018
Severity of illness	-0.035‡	0.012	-0.019	0.018	-0.002	0.013	0.041†	0.017	0.015	0.017
Income	0.006	0.006	-0.025‡	0.009	0.022‡	0.007	0.028‡	0.008	-0.031‡	0.009

Subscript ‡, † and * represent significance at the 1%, 5% and 10% levels, respectively.

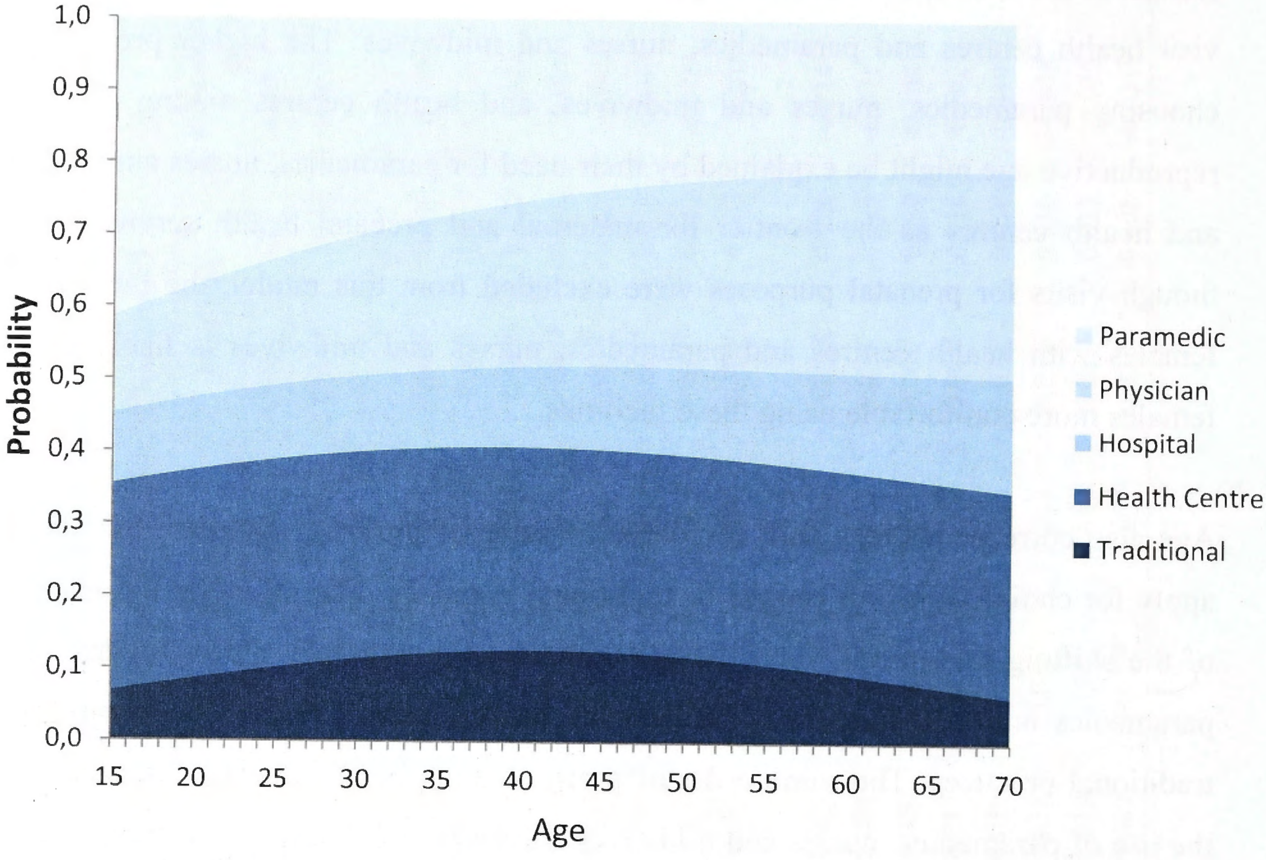
C.1. Demographic Factors

Gender is associated with choice of provider. Females are more likely than are males to visit health centres and paramedics, nurses and midwives. The higher probability of choosing paramedics, nurses and midwives, and health centres among females at reproductive age might be explained by their need for paramedics, nurses and midwives and health centres as the frontier for maternal and prenatal health services.[22] Even though visits for prenatal purposes were excluded from this model, the familiarity of females with health centres and paramedics, nurses and midwives is likely to make females more comfortable using these facilities.

Age also corresponds to a shift in people's choice of provider, although this does not apply for choice of health centres or traditional practices. The effect on the magnitude of the shifting is especially specific for each sex. For example, among males age 15, paramedics are the top choice, followed by health centres, physicians, hospitals and traditional practices. The same order of preference applies for females. As males age, the use of paramedics, nurses and midwives decreases, while the use of physicians and hospitals increases. As a result, at age 70+, physicians are the top most visited healthcare provider for men, followed by health centres and hospitals. For elderly males, paramedics, nurses and midwives and traditional practices have moved to the bottom of the list. Although the use of physicians and hospitals also increases with age among females, the magnitude of the increase is weaker. Entering age 70+, the order of preference, in descending order, is health centres, physicians, paramedics, nurses and midwives, hospitals and traditional practices.

[22] Outpatient visits for prenatal service purposes are excluded from the model. Therefore, females' familiarity with paramedics and health centres explains females' preferences in this direction at reproductive age.

Figure 5.6 Predicted probability of utilising healthcare provider for males and females by age



The increased use of physicians and hospitals/clinics can be explained in part by the fact that hospitals and clinics provide a wider range of medical care services due to the availability of doctors, and in many cases boast superior skill in curative care (Barber et al., 2007), making them more appealing for older people. Physicians offer authority in handling various diseases through consultation and treatment of chronic diseases, which are also more prevalent among the elderly.

Choice of provider might also be impacted by severity of illness as one of indications of health needs. For example, as people are getting older, frailty leads to preference of physician for their medical skill. In this study, to isolate the effect of age from health needs, severity of illness is also included in the model[23], so that the effect of age is by the way of severity of illnes. As shown by the model estimates, the significant effect of

[23] Discussion on the role of severity of illness is addressed in Section C.6 Health Needs in this thesis. The model estimates show the significant effect of severity of illness to the choice of provider.

age to the choice of providers indicates difference preference to choice of provider by age of the patients.

The inclusion of severity of illness in the model as an independent variable implies that older people prefer to choose physicians more than traditional providers, nurses and health centres, regardless of their severity of illness. It should be noted however, that in this model, information on the types of disease often contracted by patients is not available in the IFLS data and hence is not included the model. Therefore, whether the differences in the types of disease by age influences the choice of provider is not clearly known, although some data indicate the possibility of this relationship. National Basic Health Survey (Riskesdas 2007) indicates that types of disease and causes of death are specific by age groups. For example the dominant causes of death among people aged 15-44 years are accident, tuberculosis and malaria; while the causes of death among people aged 45 and above are mainly stroke, ischemic heart disease, hypertension dan diabetes (NIHRD, 2007).

Referring to the magnitude of the coefficient and AME, sex is one of the most influential variables in the choice of provider, although this relationship is not straightforward. Sex also interacts with other factors, such as the age of the respondents (see Figures 5.7 and 5.8).

Figure 5.7 Probability of choosing a particular healthcare provider among females, by age

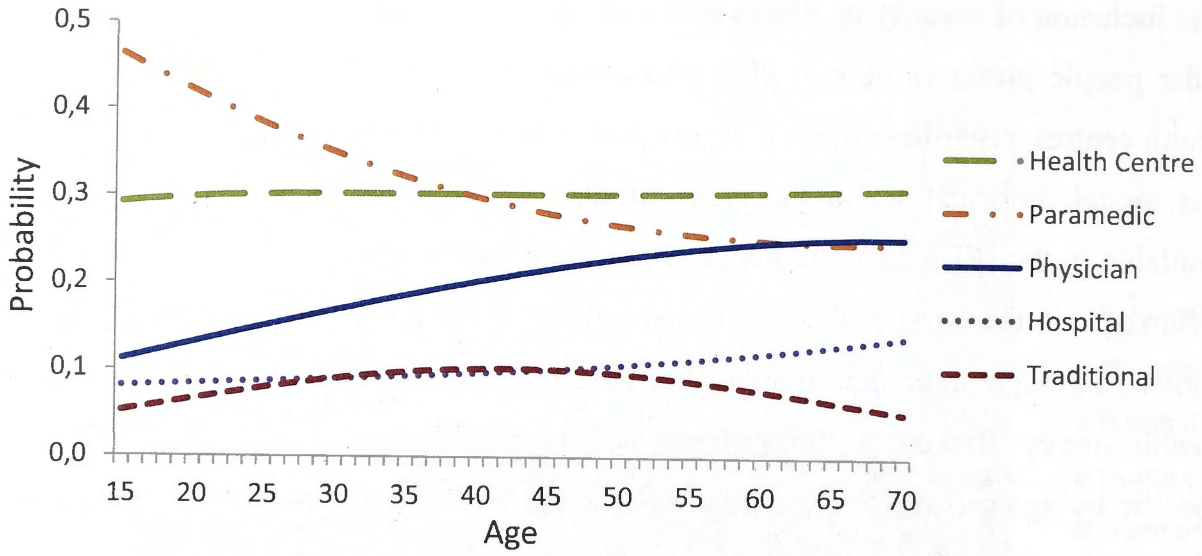
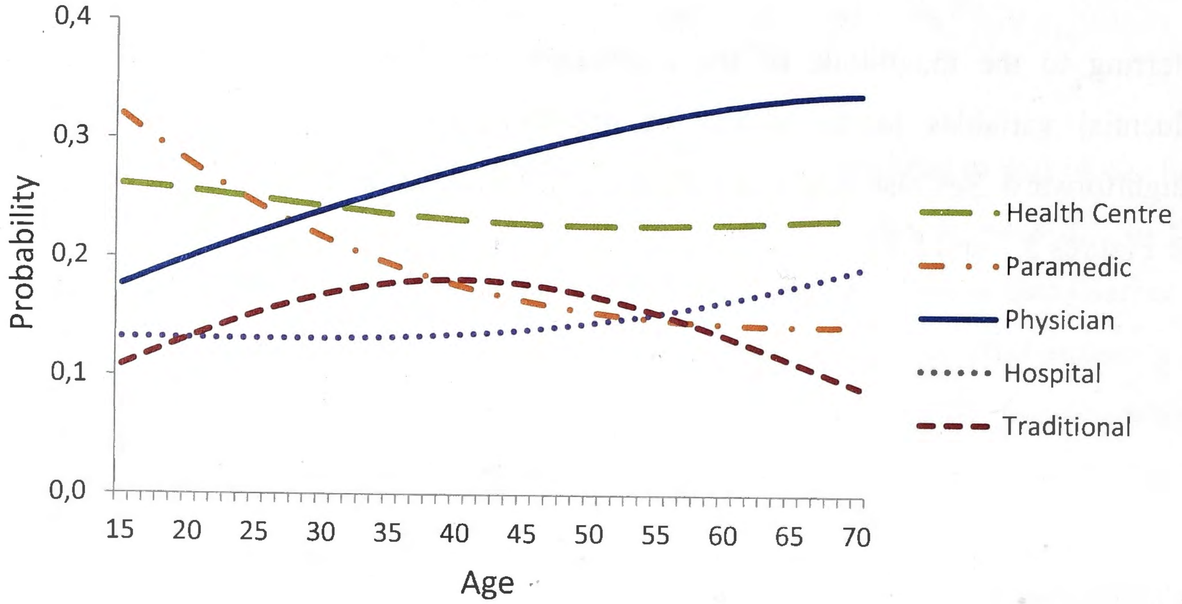


Figure 5.8 Probability of choosing a particular healthcare provider among males, by age



In contrast, marital status and householder status, in general, do not play a significant role in the choice of provider. The only exception is paramedics, nurses and midwives, which a married person is more likely to choose. Thus, even though marriage and householder status are strongly associated with the decision to seek care, as described in Chapter 4, these factors do not influence choice of provider.

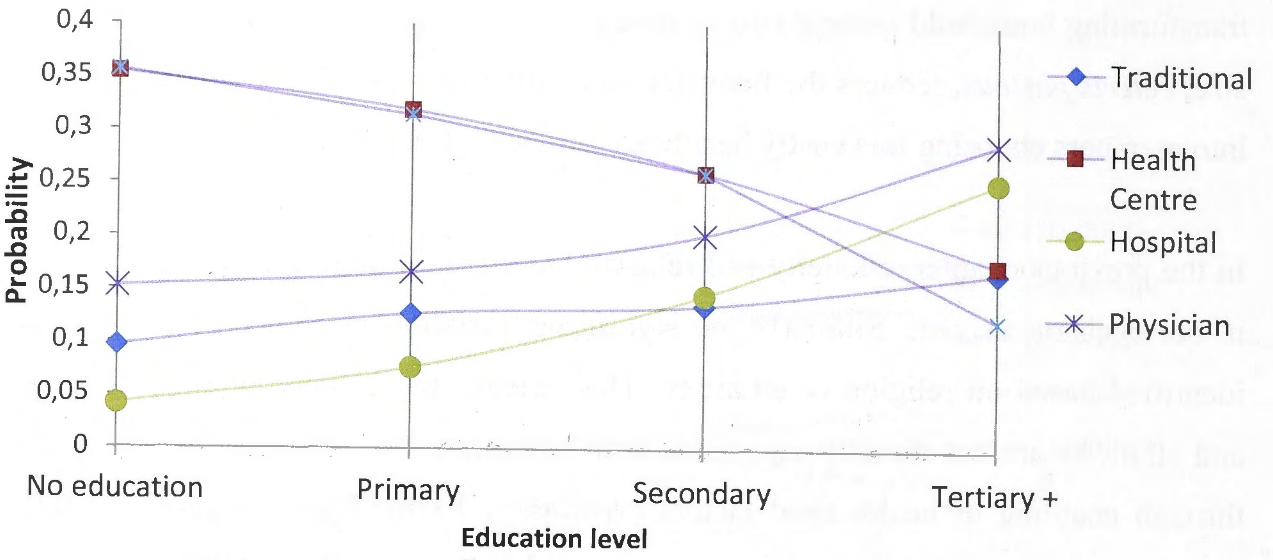
Household size does not exhibit a meaningful association with the decision to seek medical care. However, regarding choice of provider, those living in larger households are more likely to choose health centres and less likely to choose physicians. One possible explanation is that household size acts as a control for household income, transforming household income into income per capita. In this sense, a larger household size, *ceteris paribus*, reduces the financial capability of an individual, and this translates into members choosing less costly healthcare providers (that is, health centres).

In the previous chapter, ethnicity and religion were found not to play a significant role in the decision to visit. Similarly, no significant variation in choice of provider was identified based on religion or ethnicity. This extends the earlier finding that religion and ethnicity are not directly associated with healthcare use, although they may work through enabling or health need factors (Wolinsky, 1978). The implication of this is that, from a human rights perspective, inequity of access to quality healthcare providers is not a matter of ethnicity or religious affiliation.

C.2. Education Level

The choice of provider is associated with the healthcare-seeker's education level. Figure 5.9 shows that those people with lower education levels tend to choose paramedics, nurses and midwives and health centres over other providers. At higher education levels (tertiary education and above), the order of preference is reversed, and physicians and hospitals are the most visited providers, while paramedics, nurses and midwives are the least visited. On average, choice of traditional providers, on the other hand, only changes slightly (not statistically significant).

Figure 5.9 Predicted probability of provider choice by education level



It is also important to note that the association of eduction and choice of provider gets stronger as education level increases, especially from secondary to tertiary level. This suggests that people with a tertiary level of education have a significantly different attitude toward choice of provider than does the rest of the population. Previous studies using the 1997 IFLS data show similar results (Lance, 2003). Higher education level is associated with high utilisation of modern providers (doctors, clinics and health centres) and lower utilisation of paramedics, nurses and midwives. The difference is that, in 2007, the use of health centres decreased with higher education level. Therefore, as compared to one decade earlier, highly educated people are now leaving health centres in favour of hospitals and physicians. The interaction between gender and education level is not significant for any choice in this model.[24]

This result is quite different from the finding in the logistic model, which found eduation level as tending to have more of an effect among males than females in determining whether to seek medical care for illness. In other words, education's effect is more influential on choice of provider than it is on decision to visit.

[24] A separate regression was run with the additonal of interaction between education level and gender. The result is not presented here.

C.3. Income Level

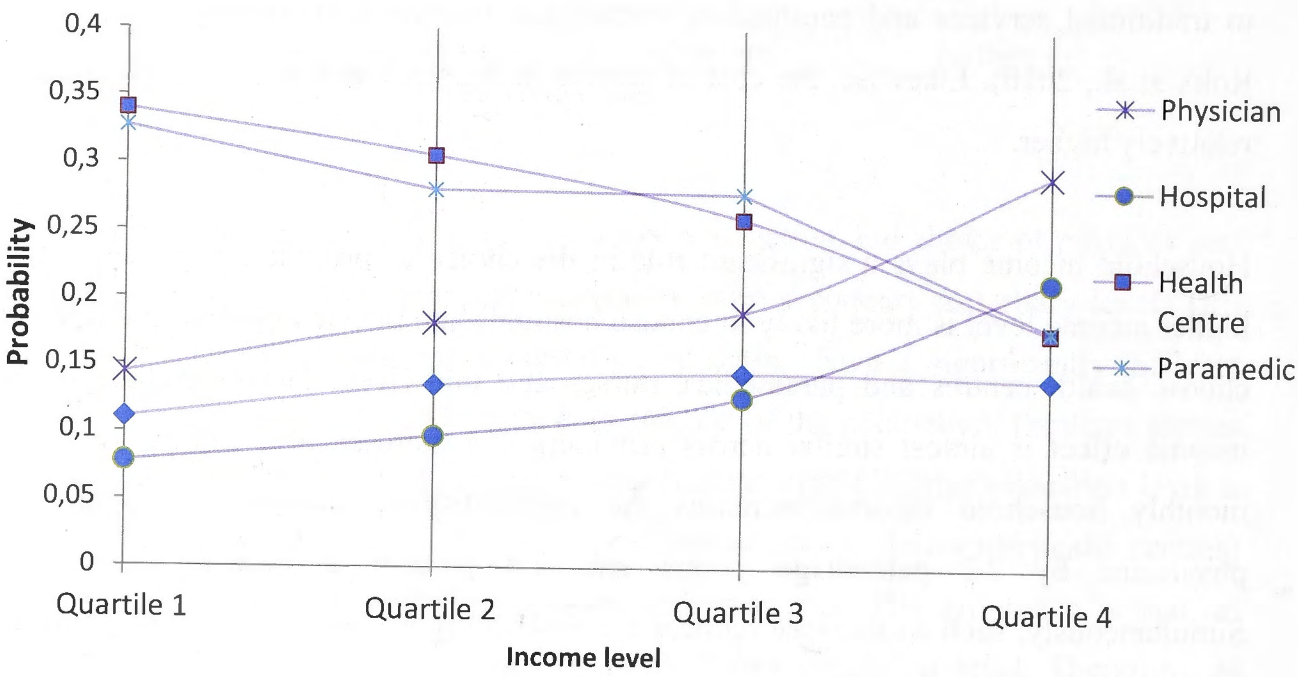
Assessing the effects of social economic status (SES) on choice of provider is important because it reflects the general issue of accessibility to quality healthcare. It also enables the examination of whether lower SES population groups have equitable access to certain types of high-quality healthcare providers. It should be kept in mind that the categorisation of the healthcare provider types into five groups in this section carries stereotypes in terms of cost and quality of service. Hospitals, physicians and health centres, for example, are regarded as providing a better quality of service as compared to traditional services and paramedics, nurses and midwives (Hennessy et al., 2005, Rokx at al., 2010). Likewise, the cost of service in hospitals and physician practices is relatively higher.

Household income plays a significant role in the choice of provider. A person with a higher income level is more likely to choose hospitals and physicians, and less likely to choose health centres and paramedics, nurses and midwives. The magnitude of the income effect is almost similar across providers. An increase of 1 million rupiah in monthly household income increases the probability of choosing hospitals and physicians by 2.2 percentage points and 2.8 percentage points, respectively. Simultaneously, such an increase reduces the probability of choosing a health centre or paramedic by 2.5 and 3.1 percentage points, respectively. Income does not have any significant effect on the choice of traditional practices. The effects of income do not vary with gender or with age. (The interaction effect is evaluated using Wald or the likelihood ratio test with p-value <0.01).

In this model, income enters the model in a linear fashion. Therefore, it is assumed that an increase of one unit in income will have a similar effect on the change in probability of choosing a particular healthcare provider regardless of income level. Previous studies show that this might not be the case. Studies by Sahn et al. (2003) in Tanzania, Grobler and Stuart (2007) in South Africa, Borah (2006) in rural India and Qian et al. (2009) in rural China show that the effect decreases by income level. In other words, income elasticity is larger in the lower income groups.

Figure 5.10 presents the effect of income level on the choice of provider. In this graph, instead of being continuous, income enters the model through a dummy variable indicating one of four income quartiles. With this specification, the model does not necessarily assume linearity of effect between income quartiles. Consequently, we can compare the 'elasticity' of income in the choice of provider; that is, estimating whether the effect of income is constant across income level.

Figure 5.10 Predicted probability of choosing a provider by income quartiles



Patients from the lowest income level (Quartile 1) are more likely to visit health centres and paramedics, nurses and midwives than they are other providers. In these two facilities, the cost of service is usually lower. Conversely, and as expected, as income rises, the preference towards health centre and paramedics, nurses and midwives decreases, while the preference towards hospitals and physicians increases. For the top income levels, physicians and hospitals are the most chosen healthcare providers. The graph also clearly shows the non-linearity of the income effect, most notably between Q3 and Q4, indicating that 'elasticity' occurs at the higher levels of income.

The positive association between higher income and choice of hospitals and physicians is more likely related to the quality and cost of services. Generally, hospitals and physicians offer a wider range of services or are more specialised, which in turn is associated with a higher cost of service. Quality and specialisation is naturally preferred by all population groups. However, only the high-income groups can manage the cost constraints. Since there is no variable relating to the cost[25] of service, these hypotheses cannot be tested in this MNL model. The next section of this chapter offers further discussion on the role of cost and service quality in choice of provider.

Related to the previous findings on the association between higher education level and use of hospitals and physicians, this result indicates that rich and educated people are more likely than are others to choose physicians and hospitals, while the poor and uneducated choose health centres and paramedics, nurses and midwives. If we consider the effects of education and income on healthcare utilisation (see Chapter 4), population groups that are less educated and have lower income levels are less likely to seek medical care when sick. When they do seek care, they are more likely to compromise on quality of care to fit their limited disposable household income.

To explore the gradient effect of income by education level, education-income interaction is added as an independent variable in the model. The result shows that the interaction is not statistically significant. Therefore in the case of this model, the effect of income to the choice of provider is not different for various levels of income. To author's knowledge, there is no study in a multinomial model of choice of health care provider investigating the effects of interaction between education and income level of the patient.

Although computation of interaction effects in logit and probit models is possible (Norton, 2004), making a simple summary measure of the interaction effect in a nonlinear model is difficult. Its marginal effect is not constant over its entire range (Mandiç, et al., 2012) and its magnitude is conditional to level of the covariates (Ai and Norton, 2003). In addition, with regard to the model used in this thesis, complexity of education-income interaction arises significantly[26]. Thus, following suggestion by

[25] Cost of medical care does not refer only to the price of service. It is also attributed to the transportation cost a person has to bear to visit a health facility and the opportunity from travel time to and waiting time in the health facility.

[26] One of the limitations in this MNL model is its relatively smaller sample size (2,895 individuals). Adding education-income interaction into the model resulted in an addition of 16 (4 levels of education by 4 of income quartiles) independent variables. Furthermore, the

Greene (2010) that testing interaction effects in a nonlinear model is less informative, education-income interaction is omitted from empirical analyses and discussion focuses on the main effects of education and income, instead.

C.4. Health Insurance

Before examining the effect of health insurance subscription, it is important to emphasise again that, throughout this thesis, two different categorisations are used in this respect. The first is whether a person is subscribed to any health insurance, as measured by insurance subscription rate. Second, what type of health insurance does the person hold: consisting of not insured, Askes (for civil servants and the military forces), Askeskin (social insurance for the poor) and private (commercial and voluntary) health insurance.

Health insurance is associated, either positively or negatively, with choice of provider. Being subscribed to health insurance is associated with a reduced use of traditional services, private physicians and paramedic, nurse and midwife practices, and increased use of hospitals and health centre services. The biggest reduction corresponding to health insurance subscription (by 12.9 percentage points) is in visits to paramedic, nurse and midwife practices (see Table 5.5).

Most health insurance policies, except for community-managed funds, which have a limited coverage anyway, do not cover the cost of services from paramedics, nurses and midwives and traditional practices. Consequently, we can expect that the use of health centres, physicians and hospitals is highly associated with health insurance subscription, since they are the preferred providers.

---

interactions need to be analyzed within 5 choices of provider. These added variables will reduce degree of freedom dan increase confidence interval of the coefficient of estimates

Table 5.5 The average marginal effect of health insurance subscription

Providers	AME	AME in %	SE	P>z	95% CI	
					Lower bound	Upper bound
Traditional	-0.021	-2.1	0.012	0.097	-0.045	0.004
Health centre	0.082	8.2	0.017	0.000	0.048	0.116
Hospital	0.093	9.3	0.012	0.000	0.068	0.117
Physician	-0.025	-2.5	0.016	0.127	-0.057	0.007
Paramedic	-0.129	-12.9	0.018	0.000	-0.165	-0.093

Relying only on the first categorisation (that is, insured and uninsured) is useful when examining the aggregate effect of health insurance. A more detailed categorisation of health insurance subscription is necessary, however, if we want to understand how health insurance actually shifts the choice of providers. Further differentiation into the types of health insurance can explain this effect.

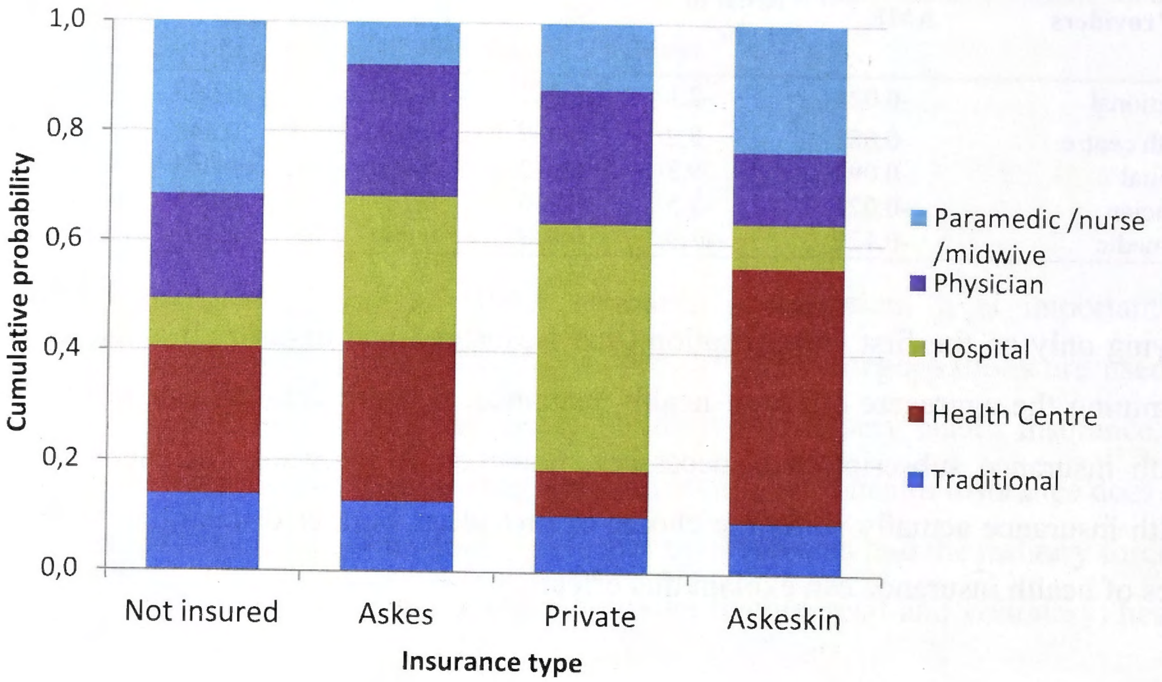
Three types of insurance, Askes, Askeskin and private insurances, affect the choice of provider in different ways, mainly because they are designed to target different population groups, and have different preferred healthcare providers. Askes (and Asabri) is mandatory insurance for civil servants and the military forces;[27] Askeskin is a social insurance for the poor, funded by the government; and private health insurance is voluntary and semi-voluntary.

When the 2007 IFLS survey was conducted, Askes and Askeskin could be used mainly in public providers (health centres and public hospitals), while most private health insurance could be used mainly in private health facilities. Therefore, effects on choice of provider can be expected to vary by insurance type. The AME of each type of health insurance on choice of providers is presented in Table 5.5. Figure 5.11 presents the effect of health insurance subscription status by predicting the probability of choosing each type of healthcare provider.[28]

[27]Asabri is a mandatory health insurance for the military forces and their close family members. The preferred provider is public health facilities including health centers and public hospitals. The similarity in nature with Askes will make the analysis less complicated when it is grouped in one category with Askes.

[28] The sum of probability is 1. Therefore, since the choice of health provider is mutually exclusive, an increase in probability of choosing a certain health provider will reduce the probability of choosing another health provider.

Figure 5.11 Predicted probability of choosing healthcare providers by type of health insurance subscription

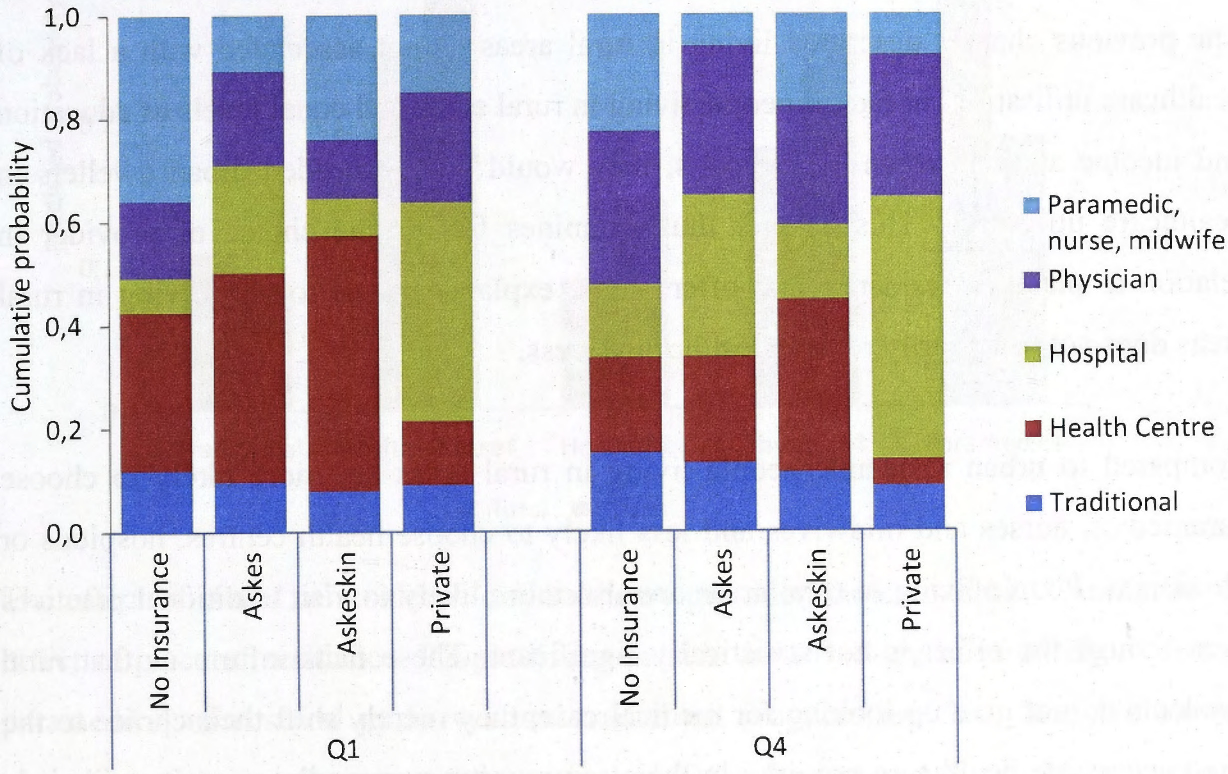


Type of insurance has a profound effect on the choice of provider. Being subscribed to Askes is associated with a significant increase in hospital service use and significantly less paramedic, nurse and midwife use. Askeskin, on the other hand, is associated with increased used of health centres and decreased use of physicians. Another marked difference is the strong and positive association of use of hospitals and private health insurance subscriptions.

Most of the effects of health insurance were anticipated by reviewing the preferred providers as described previously. What is unclear from this graph is the interaction effect of health insurance subscription with income or other financial characteristics of health services. This topic is quite important for analysing the effectiveness of health insurance as a mean to reduce out of pocket expenditure, and for determining whether health insurance is able to increase the use of high-quality health services, especially among lower income groups.

Figure 5.12 maps the association of health insurance subscription and provider choice between two extreme population groups in terms of income level. Quartile 1 (Q1) represents the 25% lowest income population group, and Q4 is the 25% highest income population group. This figure assumes that the effect of health insurance on the other income level population lies between these two extremes. It should be noted that although Askeskin is intended for the poor, due to some leakages in the distribution mechanism, small proportion of population in Q4 are also benefitted from Askeskin.

Figure 5.12 Probability of choosing healthcare provider by insurance type for two income groups, Q1 and Q4



The effect of income level on healthcare utilisation was described in Section C.3 of this chapter, with the general conclusion that higher income is associated with increased use of hospitals and physicians and lower use of paramedics, nurses and midwives and health centres. Figure 5.12 shows that the effect of health insurance is similar regardless of income level. In statistical terms, the interaction effect of health insurance and income level is not significant. To validate this visual interpretation, the interaction of health insurance and income level was entered into the MNL model and their effects were tested using a Wald test. Results show that the interaction effect is not significant for any type of provider.

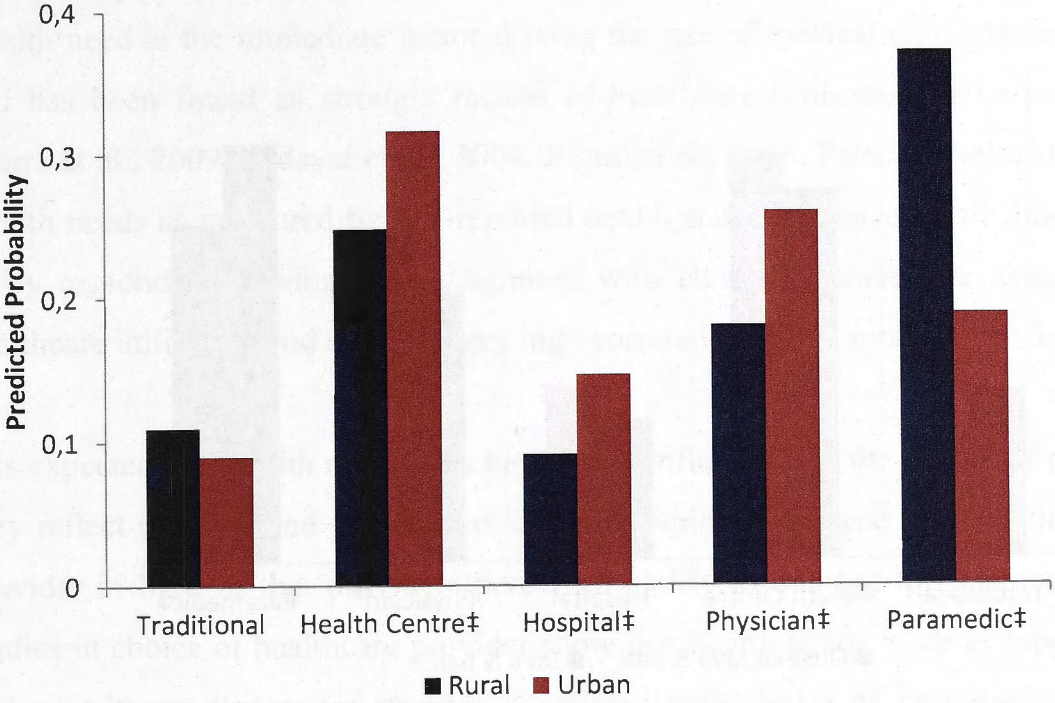
From the public policy perspective, the results show that health insurance influences the choice of provider for all income brackets, not just those at the lower income level. For the poor, the effect is likely brought by social health insurance (Askeskin), which increases the use of health centres. Askes holders have higher use of health centres and hospitals, while people subscribed to private health insurance use hospitals more and health centres less. Health insurance subscription does not affect use of traditional practices, nor is use of traditional practice affected by level of income.

C.5. Place and Island of Residence

The previous chapter described living in rural areas as not associated with a lack of healthcare utilisation. In fact, if people living in rural areas had equal levels of education and income as their urban counterparts, they would have exceeded urban dwellers in healthcare utilisation. This chapter thus examines further the choice of provider in relation to place of residence and offers some explanations as to why living in rural areas does not necessarily reduce healthcare access.

Compared to urban residents, people living in rural areas are more likely to choose paramedics, nurses and midwives and less likely to choose health centres, hospitals or physicians. People living in rural areas are also more likely to visit traditional practices even though the effect is not statistically significant. These facts inform us that rural residents do not give up looking for medical care; they merely shift their choice to the most accessible healthcare provider in their community: paramedics, nurses, midwives or traditional practices. In regard to health centres, even though most subdistricts have at least one health centre and an auxiliary health centre, their locations are relatively further away for most households or cannot be easily accessed by transportation.

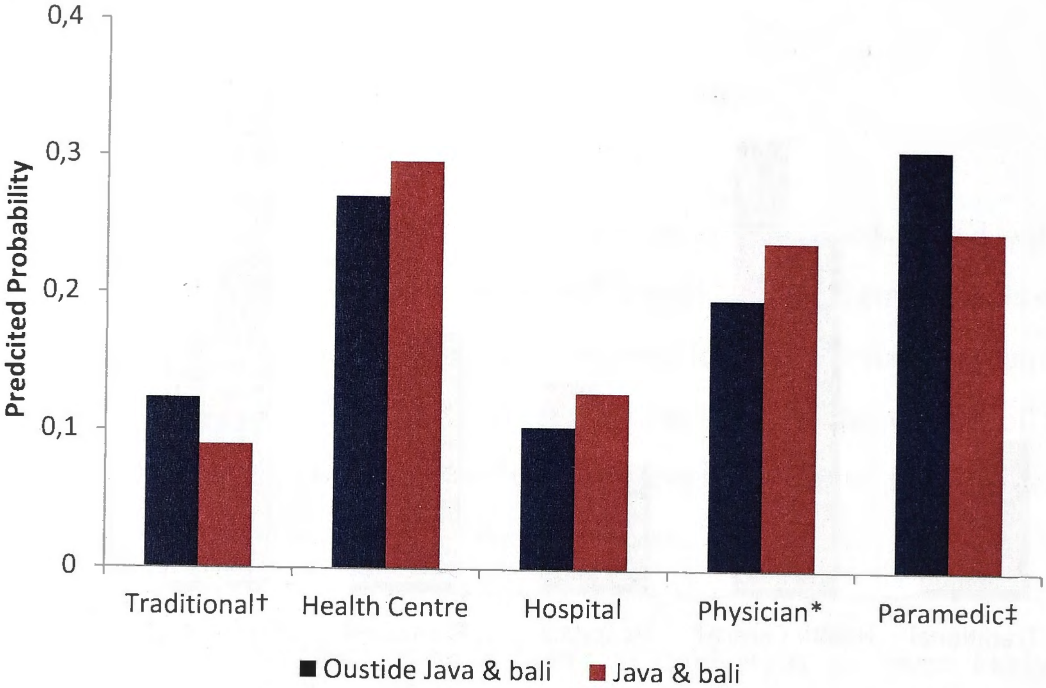
Figure 5.13 Predicted probability of choosing a healthcare provider, by place of residence



The effect of island of residence on healthcare provider choice is almost similar to the effect of place of residence. People living outside Java/Bali are more likely to choose paramedics, nurses and midwives and traditional practices and less likely to choose physicians than are their counterparts in Java/Bali. However, paramedics, nurses and midwives is the only choice that is statistically significant, while the effect for traditional practices and physicians is only marginal. Therefore, although both place and island of residence represent the overall development achievement of a region, the effect of the urban–rural differential on choice of provider is more profound than the effect of living in or outside Java/Bali.

The interaction effect between place and island of residence is not statistically significant (p>0.1), and therefore the effect of rural and urban residence is consistent, regardless of island of residence and *vice versa.* This means that people living in rural areas outside Java/Bali have the highest probability of choosing paramedics, nurses and village midwives to meet their healthcare needs. In the other extreme, people living in urban areas on Java/Bali have the highest probability of choosing physicians, hospitals and health centres when they are sick.

Figure 5.14 Predicted probability of choosing a healthcare provider, by island of residence



The findings in Chapter 4 on healthcare utilisation suggest that the utilisation of healthcare services in rural areas is not lower, but that this is the case for people living outside Java/Bali. When a connection is made between healthcare utilisation and choice of provider, it can be concluded that people living in rural areas are not disadvantaged in healthcare utilisation, but they do shift their choice of provider. However, people living in rural areas outside Java/Bali do experience lower rates of healthcare utilisation due to the reasons outlined in Sections C.4.3 and C.4.4 of Chapter 4, as well as the lower quality of service offered by paramedics, nurses and midwives, which in general only provide basic healthcare services.

Again, the extent of the disparity of healthcare utilisation and choice of provider between place of residence and island of residence is underestimated at the national level by the 2007 IFLS data. Recalling Figure 4.2, two barriers to access were travel time and distance. Had 2007 IFLS covered the more remote provinces of Maluku, North Maluku, Papua and East Nusa Tenggara, the effect of place and island of residence might have been more profound.

C.6. Health Needs

Health need is the immediate factor driving the use of medical care (Andersen, 1995) and has been found as strongly related to healthcare utilisation in various contexts (Berra et al., 2009, Hidayat et al., 2004, Rosenstock, 1966, Palacio-Vieira et al., 2012). Health needs as measured by self-reported health status and severity of illness, as well as by respondents having been diagnosed with chronic diseases are associated with healthcare utilisation and also has very high correlation in this model (see Chapter 4).

It is expected that health needs also have some influences on the choice of provider, as they reflect the type and intensity of sickness, which in the end leads to the choice of provider in light of that providers perceived ability to manage the sickness. Previous studies in choice of healthcare provider show that health needs, such as type of disease and severity of illness, are strongly associated with choice of provider (Grobler and Stuart, 2007, Yip et al., 1998). Generally, acute or more severe illness leads to choosing health facilitates with a higher capability for handing and managing sickness.

In Table 5.2, general health status has effects on provider choice. People with poorer health status tend to prefer hospitals and physicians to traditional practices and health centres. Likewise, the severity of illnesses is negatively associated with the choice of traditional practices while also having a marginally positive association with preference towards physicians. This suggests that people with more severe illnesses are more likely to forgo traditional healing in favour of formal healthcare services, which usually provide modern treatment and medicine. Moreover, patients with severe illness are more likely to visit hospitals and health centres (p-value <0.05). These patterns prevail regardless of gender, income level or region of residence ($p< 0.01$ and $p<0.05$ level).

The most obvious difference between the characteristics of traditional practices and other healthcare providers is their lack of health workers, modern drugs and equipment. This implies that when people are faced with a serious need for medical care due to severe illness, their response is choosing healthcare providers that offer better quality of care. However, this cannot be proven in this model since quality characteristics of each alternative variable cannot enter the model without introducing bias. The effect of healthcare providers will be investigated further with the RPL model (see Chapter 6), which accommodates alternative-specific characteristics.

According to 2007 IFLS, about 39.4% of adults aged 40 years and above have been diagnosed by health professionals as suffering from at least one chronic disease (hypertension, diabetes, stroke, cancer, coronary heart diseases or others). The rate of chronic diseases increases with age, from 26% at age 40–44 to 52% at age 75+. The data shows that sick adults with chronic diseases have a higher healthcare utilisation rate (28.6%) as compared to adults without chronic diseases (13.1%). As described in Chapter 4, after controlling for other factors, diagnosis with a chronic disease increases the odds ratio of utilising healthcare (including traditional care) by 97%. Since diagnosis is made by medical professionals, this type of health need factor is categorised as an evaluated health need. In this section, the effects of chronic diseases will be briefly analysed and referred to as an evaluated health need (in contrast to self-reported health status, which is termed a perceived health need).

To compare the effect of evaluated health needs with perceived health needs, a new variable (being diagnosed with at least one chronic disease) was introduced into the model. In 2007 IFLS, this variable is available only for respondents aged 40 years and older (N=1,403). To reduce standard errors in the estimations, variables that do not exhibit significant effects at 0.01 levels, as determined by a likelihood ratio test, should be excluded from the model. As a result, the following variables were excluded: age squared, marital status, householder status, household size, religion and ethnicity. The result from the MNL model with the remaining variables is presented in Table 5.6

While poor health has a significant effect on the choice of hospitals and physicians as compared to traditional practices, having a chronic disease does not have any significant effect on likelihood of choosing any type of provider as compared to traditional practice. However, this interpretation is relative to the base reference (that is, traditional practices), and therefore the whole effect depends on the behaviour of the reference. A likelihood ratio test can be used to evaluate whether the effect of a variable adds more explanation to the model (Scott and Freese, 2006).

Table 5.6 Estimate of the coefficient of reduced MNL model

Variables	Health centre		Hospital		Physician		Paramedic, nurse, midwife	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Age	0.021*	0.011	0.040‡	0.013	0.032‡	0.011	0.017	0.011
Sex	0.087	0.226	-0.423*	0.253	-0.398*	0.230	0.338	0.236
Education	-0.005	0.172	0.447†	0.193	0.213	0.175	-0.253	0.182
Index of facility knowledge	-0.181‡	0.064	-0.086	0.073	-0.028	0.066	-0.100	0.065
Askes	0.065	0.312	0.430	0.338	-0.409	0.321	-1.328‡	0.389
Askeskin	0.446	0.300	0.369	0.363	-0.330	0.330	-0.479	0.320
Private	-0.841	0.730	2.045‡	0.577	0.485	0.590	-1.462*	0.887
Region of residence	0.006	0.226	-0.392	0.265	0.105	0.234	0.853‡	0.237
Island of residence	0.625‡	0.225	0.808‡	0.260	1.225‡	0.237	0.576†	0.232
Severity of illness	-0.023	0.220	-0.029	0.252	0.403*	0.231	0.340	0.231
General health status	-0.022	0.232	0.685‡	0.262	0.442*	0.236	0.285	0.236
Chronic disease	**0.258**	**0.219**	**0.133**	**0.253**	**0.276**	**0.227**	**-0.212**	**0.225**
Income	-0.068	0.045	0.020	0.043	0.059	0.038	-0.008	0.044
Constant	0.610	0.843	-2.704‡	0.977	-2.118†	0.878	-0.063	0.870

N= 1,403, Log likelihood: -1934, Pseudo R2=0.1008. Subscript ‡, † and * represent significance at the 1%, 5% and 10% levels, respectively

Table 5.7 The estimate of likelihood ratio test of the model

Variable	chi^2	Df	P>chi^2
Age	13.696	4	0.008
Sex	22.797	4	0.001
Education	20.992	4	0.001
Index of facility knowledge	14.878	4	0.005
Askes	34.58	4	0.001
Askeskin	26.301	4	0.001
Private	58.489	4	0.001
Region of residence	41.122	4	0.001
Island of residence	30.594	4	0.001
Severity of illness	11.333	4	0.023
General health status	16.494	4	0.002
Chronic disease	10.542	4	0.032
Income	16.526	4	0.002

The likelihood ratio test shows that chronic disease is only marginally significant (p-value <0.05) and less pronounced compared to perceived health status (p-value <0.001). In other words, generally, the effect of perceived health status is stronger than for evaluated health need. However, this marginality of the effect indicates that evaluated health needs might have significance to certain types of choice. Table 5.8 compares the AME of perceived and evaluated healthcare needs for each type of provider.

Table 5.8 Average marginal effect of perceived health and evaluated health status

Healthcare provider	General health status		Chronic disease	
	AME	SE	AME	SE
Traditional	-0.022	0.017	-0.009	0.016
Health centre	-0.075‡	0.025	0.043*	0.025
Hospital	0.050‡	0.018	-0.001	0.018
Physician	0.036	0.023	0.037	0.024
Paramedic	0.012	0.023	-0.069‡	0.022

Notes: subscript ‡, † and * represent significance at the 1%, 5% and 10% levels, respectively

Table 5.8 shows that, on average, having been diagnosed with at least one type of chronic disease reduces the probability of choosing paramedics, nurses and midwives by 6.9% and increases the probability of choosing health centres and physicians by 4.3% and 3.7%, respectively. In contrast, a self-assessed poor health condition reduces the probability of choosing health centres by 7.5% and increases the probability of choosing hospitals by 5.0%.

Patients who are in poor health or who have been diagnosed with at least one type of chronic disease are less likely to choose traditional practices, and more likely to choose hospitals and physicians. However, they show opposing trends in terms of likelihood to choose health centres, and paramedics, nurses and midwives. While people with poor health conditions (perceived) are less likely to choose health centres in favour of paramedics, nurses and midwives, having been diagnosed with a chronic disease (evaluated) reduces the likelihood to choose paramedics, nurses and midwives in favour of health centres. It is also worth noting that this response behaviour is also different by place of residence and island of residence. Figures 5.15 and 5.16 show the effect of place and island of residence on healthcare provider choice.

Figure 5.15 Predicted probability of provider choices among persons diagnosed with a chronic disease, by place of residence

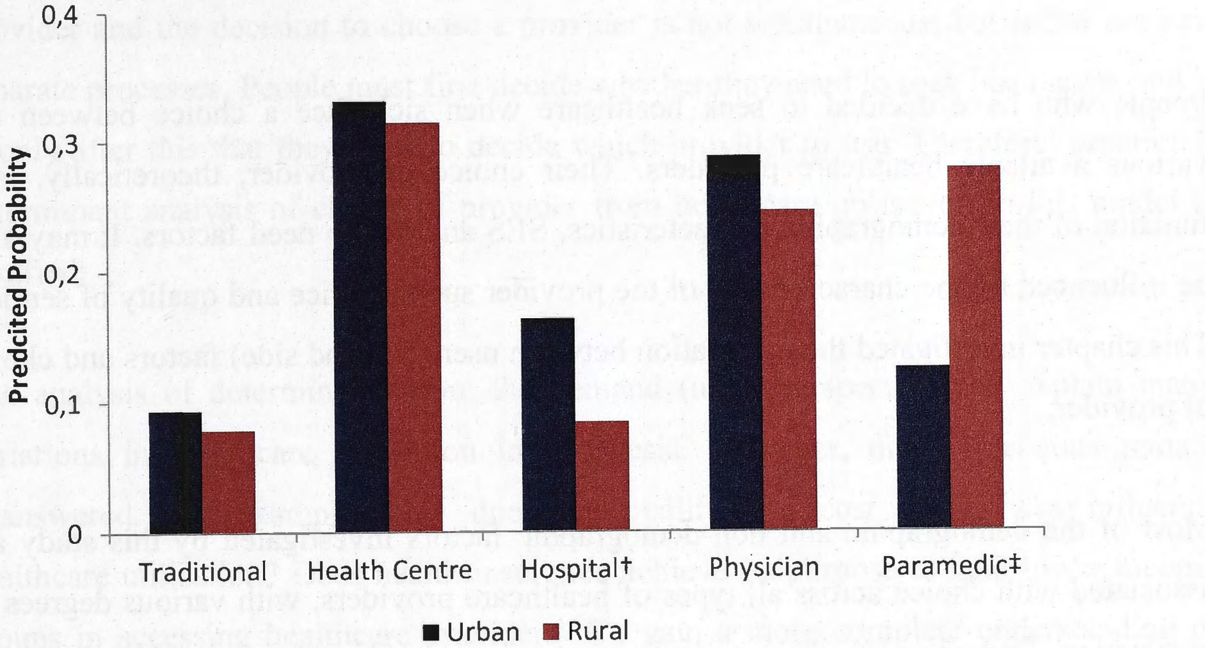
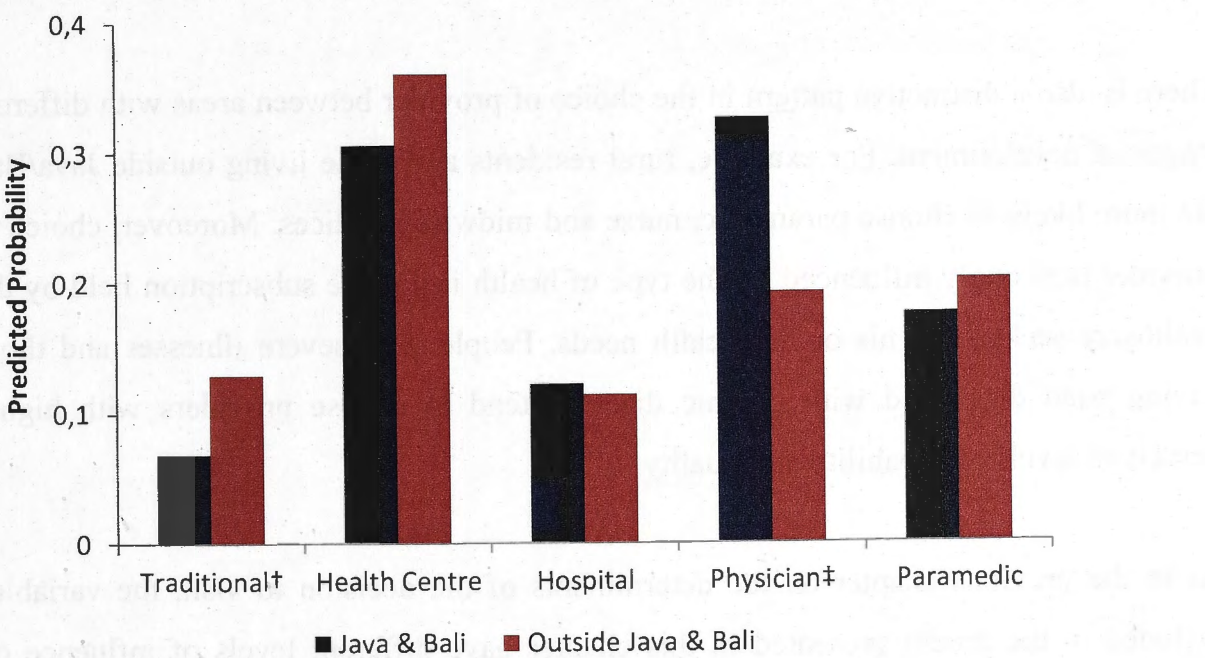


Figure 5.16 Predicted probability of provider choices among persons diagnosed with a chronic disease, by island of residence



The most noticeable difference between the effect of place of residence (urban and rural) and island of residence (Java/Bali) is the choice of health centres and traditional practices. The difference in the response to chronic disease between urban and rural place of residence is in the choice of hospitals and paramedics, nurses and midwives. The difference between islands of residence is the visits to traditional practices and physicians.

D. Summary

People who have decided to seek healthcare when sick face a choice between the various available healthcare providers. Their choice of provider, theoretically, is a function of their demographic characteristics, SES and health need factors. It may also be influenced by the characteristics of the provider such as price and quality of service. This chapter investigated the association between user (demand side) factors and choice of provider.

Most of the demographic and non-demographic factors investigated by this study are associated with choice across all types of healthcare providers, with various degrees of association. Demographic characteristics, such as sex, age and household size, but not religion and ethnicity, are important in influencing the choice of providers. Healthcare-seekers from higher SES backgrounds (that is, with higher education and income levels) are more likely to choose higher quality providers such as hospitals and physicians.

There is also a distinctive pattern in the choice of provider between areas with different stages of development. For example, rural residents and those living outside Java/Bali are more likely to choose paramedic, nurse and midwife practices. Moreover, choice of provider is strongly influenced by the type of health insurance subscription held by the healthcare-seeker and his or her health needs. People with severe illnesses and those having been diagnosed with chronic diseases tend to choose providers with higher perceived levels of capability and quality.

As in the previous chapter on the determinants of the decision to visit, the variables included in the model presented in this chapter have different levels of influence on choice of provider. For example, place of residence (rural and urban) does not have a significant effect on healthcare utilisation, but it has a profound effect on choice of paramedics, nurses and midwives. These findings suggest that people in rural areas are not lacking in access to healthcare, but in maintaining their access, they have compromised on the quality of service they receive.

The difference in association and the degree of influence between decision to visit and choice of provider also indicates that when people are sick, the decision to visit a provider and the decision to choose a provider is not simultaneous, but rather are two separate processes. People must first decide whether they need to seek healthcare, and it is only after this that they have to decide which provider to use. Therefore, separating determinant analysis of choice of provider from healthcare utilisation in this model is justified.

The analysis of determinants from the demand (user) perspective can explain many variations in healthcare utilisation in Indonesia. However, many questions remain unanswered. For example, how does the quality and cost of services influence healthcare utilisation? Does health insurance achieve its purpose to help lower income groups in accessing healthcare providers? To gain a more complete understanding of healthcare utilisation patterns, additional analysis with a focus on the characteristics of providers is necessary.

The difference in use/choice and the deg [illegible]

choice of provider also indicates that [illegible]

provider and the decision to choose a prov [illegible]

separate processes. People must first decide wh [illegible]

is only after this that they have to decide wh [illegible]

determinant analysis of choice of provider from [illegible]

justified.

The analysis of determinants from the demand [illegible]

variations in healthcare utilisation is important. How [illegible]

unanswered. For example, how does the [illegible]

healthcare utilisation? Does health insurance reduce [illegible]

groups in accessing healthcare providers? To ans [illegible]

healthcare utilisation patterns, additional analysis [illegible]

providers is necessary.

Chapter 6
The Roles of Provider Characteristics

Previous chapters have discussed the utilisation of healthcare services and investigated their association with user characteristics. Demographic, social economic status (SES) and health needs all have some degree of influence on healthcare utilisation and choice of provider. In Chapters 4 and 5, the focus has been on user characteristics. Now, attention shifts to provider characteristics. Intuitively, healthcare provider attributes, such as price, accessibility and quality of service, also play a role in healthcare utilisation and choice of provider. These characteristics are often viewed as the barriers that can hamper access to health services (Jacobs et al., 2012).

This chapter investigates the roles of provider characteristics such as price of service, travel distance and the quality of services on choice of provider. Benefiting from facility-based modules in the 2007 IFLS, this analysis of the roles of provider characteristics is the first of its kind focusing on Indonesia, filling a significant gap in understanding the role of provider characteristics in demand for healthcare.

This chapter starts with a description of access to healthcare services in Indonesia, followed by a review of studies in this field, in Indonesia and in the international context. Next, the data sources and model development are discussed. Finally, the effects of provider characteristics and their interactions with user characteristics on the choice of provider are investigated and presented.

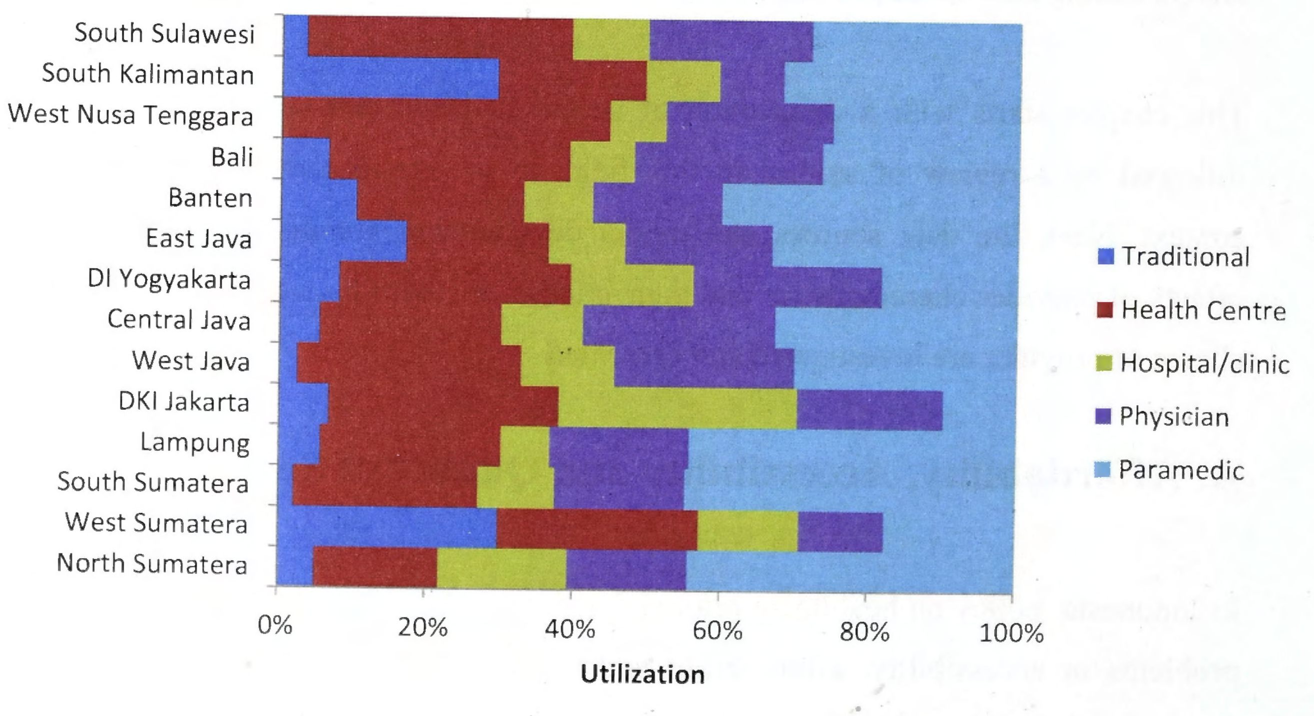
A. Affordability, Accessibility and Quality of Service

In Indonesia, policy on healthcare reforms has largely been based on the recognition of problems in accessibility, affordability and quality of healthcare services. With the adoption of the Alma Ata Declaration of Universal Access to Primary Healthcare, the first massive effort aimed to increase access to healthcare by establishing healthcare centres and auxiliary healthcare centres, providing subsidies to lower the cost of services and increasing the quality of services.

One indication on the role of provider characteristics is shown by the variability of choice of providers in the 2007 IFLS provinces (see Figure 6.1). In Jakarta and Yogyakarta, regarded as the two top provinces in overall rank of population health status and healthcare provision, the proportion of population choosing hospitals was quite high, while paramedics, nurses and midwives were chosen by a smaller proportion of the population. In these provinces, accessibility to hospitals and clinics was good.

With the idea of addressing financial and geographical barriers to healthcare utilisation, transportation subsidies for poor mothers seeking delivery services in health centres have also been offered since 2005. The government also intervened with social health insurance for the poor and near-poor population in 2005. Several studies have found positive effects for health insurance on healthcare utilisation (Hidayat et al., 2004, Sparrow et al., 2010). The effect of health insurance has also been described in this study (see Chapter 4).

Figure 6.1 Choice of provider by province, Indonesia 2007



Data source: Calculated from 2007 IFLS

However, the issue of geographic accessibility (henceforth, the term 'accessibility' will be used) persists. According to the 2007 IDHS, among ever married women who reported having problems accessing healthcare (47% of respondents), 15% specifically mentioned the problem of distance. However, whether this perceived problem is reflected in the reduction of actual healthcare utilisation is not known.

Nationally, 94% households reported residing within five kilometres of the closest healthcare facility (not including traditional practices), and only 6% reside more than five kilometres from the closest health facility. The variation between provinces and place of residence, however, is quite significant. Provinces in the eastern part of Indonesia commonly have a higher proportion of households residing more than five kilometres from the nearest health facility; for example, this is the case in East Nusa Tenggara (14.4%) and Papua (12.7%). Urban and rural difference is also noticeable. Only 1.4% of urban households reside more than five kilometres from health facilities, whereas 8.9% of rural households reported the same (NIHRD, 2007).

Variations among provinces and urban–rural localities also occur in the time needed for travel from home to healthcare facilities. Travel time measures distance but also reflects geographical difficulties and transportation availability. Households in provinces in Eastern Indonesia and those in rural areas require more time to travel to health facilities. For example, the national average of households with a travel time of more than 30 minutes is 9.3%, but the proportion in East Nusa Tenggara is 30.7% (NIHRD, 2007).

An association between accessibility and healthcare utilisation is observed in rural India (Borah, 2006), rural China (Qian et al., 2009) and some other contexts (Gertler et al., 1987, Gertler and Gaag, 1990, Mwabu et al., 1993). Previously, a study in Indonesia by Hidayat et al. (2004) found that travel time has a positive association with the use of private and public providers. This study however may suffer from selection bias, since it counted only travel time to the chosen provider and ignored information on travel time to other types of health facilities. Another study shows that distance is a significant predictor of healthcare utilisation for the uninsured rural population, but that it is not significant for the uninsured urban population (Erlyana et al., 2011).

Various cost-related barriers can hamper use of health services, such as price of service, travel cost and opportunity cost. There is strong evidence that price of service influences the utilisation of healthcare. For outpatient care, the effect of price of service on the utilisation of healthcare in the international context has largely been identified, including in studies in Côte d'Ivoire and Peru (Gertler and Gaag, 1990), rural India (Borah, 2006), rural China (Qian et al., 2009), rural Tanzania (Sahn et al., 2003) and Eritrea (Habtom and Ruys, 2007). In general, these studies have suggested that demand for healthcare is sensitive to price, especially among low-income populations.

In Indonesia, there is some thought that higher price of service hinders people from seeking medical care. Price of service is usually paid as out of pocket expenditure by consumers. To address the burden of out of pocket expenditure for healthcare utilisation, the government intervened to provide a subsidy for public health facilities; and in 2005, the government initiated the Askeskin program, which provides health insurance for the poor, with the premium paid by the government.

The 2007 IDHS provides a hint on this issue. About 25% of ever married women who reported having problems in accessing healthcare stated that cost was the cause of lack of accessibility of healthcare services (BPS and Macro International, 2008). Erlyana et al. (2011) suggested that price of service is negatively associated with healthcare utilisation for the uninsured urban population, but that this does not hold true for the uninsured rural population. Up to now, however, no empirical evidence has been presented for the role of price of healthcare on utilisation among the general Indonesian population.

Although distance can be viewed as a geographical barrier, it can impose cost, so that distance can also be approached as a cost-related barrier to service. This problem usually arises in rural and remote areas in which, due to lack of healthcare facilities, people have to spend a substantial amount of money for transportation purposes. In other countries, travel cost can be considerable and may reduce demand (Ensor and Cooper, 2004). This is the case in Zimbabwe (Fawcus et al., 1996), the Philippines (Schwartz et al., 1988), Uganda (Amooti-Kaguna and Nuwaha, 2000) and Thailand (Raghupathy, 1996).

Other measures of cost are the opportunity costs of attending care. This cost can come from patients waiting time in healthcare facilities and time to travel. Medical care services require allocation of time both for users and for carers, who often need to stop working or other activities to seek care. Consequently, earnings or leisure must be foregone. Opportunity cost is valuing time, which traditionally has been measured by forgone wages (for paid employment) or a fraction of this wage if time is taken from non-employment activities. Previous studies have found that the cost can be substantial (Akin and Hutchinson, 1999, Khan et al., 2002, Rankin et al., 2001, Segall et al., 2002). However, measuring time cost is not straightforward. Time needed to seek medical care and users' employment wages are rarely recorded.

Concern over the quality of service of providers has led the government to launch reforms in healthcare policy. For example, adequacy of facilities and skilled health workers has been identified as a major factor in achieving MDG targets on reduction of the maternal mortality rate and IMR (Bahjuri-Ali et al., 2009). The government response has been to produce more and to re-train existing health workers, and to improve the availability of essential drugs.

Quality of service can be measured by several dimensions; that is, outcome of care, process of care, the settings in which medical care takes place and the instrumentalities of which it is produced (see Chapter 4, Section A.2). In this study, quality of care adopts the third dimension of care (Donabedian, 1978); that is, in the instrumentalities of which medical care is produced, including the availability of essential drugs, the completeness of medical equipment, and the number of medical doctors in the providers. These variables are what several studies have referred to as 'availability' (Ensor and Cooper, 2004, Jacobs et al., 2012, Peters et al., 2008). In this study, the term 'quality' will be used instead, since it is closer to the term that is used in the public policy context.

B. Conceptual Framework

For analysis of the relationship between provider characteristics and choice of provider, several analytical frameworks can be used. In the behaviour model of health service use (Andersen, 1995), the issue of access to health services fits into the enabling resource factors, referring to the availability of resources both in households and at the community level to enable people to use healthcare.

Ensor and Cooper (2004), in their study of barriers to health services, offered a differentiation of demand-side and supply-side determinants. Demand-side determinants influence demand and operate at the individual, household and community levels. Meanwhile, supply-side determinants influence the slope and position of the supply curve, including price, availability, technology and management. Price, in this context, means the price needed to produce the care.

O'Donnel (2007) further elaborated on the two sides of access: the supply side (including quality) and the demand side (including poverty). Since the two are related, addressing access requires tackling both demand and supply issues. Jacobs (2012) specifies that demand-side determinants are related to factors influencing the use of healthcare services at the individual, household and community levels, while supply-side determinants are inherent to the health system.

Peters et al. (2008) developed a conceptual framework for accessing health services based on longstanding descriptions of the behaviour models of Aday and Andersen (1974) and Penchansky and Thomas (1981). There are four main dimensions of access that have supply-and-demand elements, including geographical accessibility (such as distance and travel time), availability (such as service hours), financial accessibility (such as price, willingness to pay and health insurance) and acceptability (such as responsiveness to social and individual expectation). In this model, quality of care is at the centre of the four dimensions of access.

Table 6.1 shows a framework for accessing barriers to healthcare as used in Jacobs (2012) and adapted from the earlier works of Ensor and Cooper (2004) and Peters et al. (2008). The framework reveals both the supply and demand sides as the factors that influence access to health service. The framework also recognises that the financial aspects of access involve both a supply (including cost of services) and demand side (including travel cost). In this framework, quality of care is not included as one of the four access dimensions, as it is, in fact, an important component of each dimension, related to technical ability to affect people's health (Peters et al., 2008).

Table 6.1 Health service framework, with specification of supply and demand

Supply side	Demand side
Geographic accessibility • Service location	• Travel cost • Means of transport available
Availability • Health workers, absenteeism, service hours • Waiting time • Drugs and consumable • Motivation of staff • Non-integration of health services • Lack of opportunity • Lack or no referral	• Information on healthcare providers • Education
Affordability • Cost and price of service • Private-public dual practice	• Household resources, willingness to pay • Opportunity cost • Cash flow within society
Acceptability • Complexity of the price system • Staff interpersonal skill and trust	• Household expectation • Low self-esteem and little assertiveness • Community and cultural preferences

Source: (Jacobs et al., 2012)

The categorisation of factors influencing access to healthcare into supply and demand dimensions will help in determining the roles of provider characteristics. In this study, however, the categorisation is not rigid. For example, travel cost can be attributed to demand, since it varies depending on the location of the household. However, it can also be attributed to supply, since its value also depends on the location of the provider. Waiting time indicates the extent of staff distribution and equipment, which are supply characteristics. However, wait time can also be monetised according to each individual's level of income, and be measured as an opportunity cost of care or forgone earnings due to care seeking (McPake et al., 2012). Travel distance is a further example, in that it can be attributed to individual characteristics (demand side), but is also bound to the physical location of the health facility (supply).

Thus, in this study, several characteristics (variables) will be included in the analysis, including price of service, travel distance, number of doctors and availability of drugs. Referring to Ensor and Cooper (2004), these variables are not entirely categorised as either supply or demand side characteristics. However, price of service, which is generally regarded as having a mix of supply and demand side attributes,[29] will not be

[29] In another case, price is a complex variable including direct price and distance cost, opportunity cost and any informal payment. In this study, price refers to the financial or monetised non-financial charge for a given service.

regarded as such in the context of this study. Here, it can be attributed only to supply side factors, since the data on supply side factors are averaged at the community level and thus do not vary by individual or household, but rather by type of health facility.

In statistical terms, the characteristics listed above vary by provider (that is, they are dependent variables), and are often referred to as alternative-specific attributes (Hensher and Greene, 2003, McFadden and Train, 2000). In this model, the alternative-specific characteristics are attributed to healthcare providers, and thus throughout this chapter, the term 'provider's characteristics' will be used for this.

C. Model Development

Empirical assessment of the effects of provider characteristics on healthcare utilisation is often hindered by data limitations. Most of the data in healthcare utilisation are household-based survey data, which in many cases also contain information on individual members in the household. Consequently, the data on the characteristics of providers not visited by the user are not available and have to be estimated. This can create selection bias whereby information on provider characteristics is only available for the healthcare providers visited by the sample (Gertler et al., 1987).

The advantage of 2007 IFLS is that, in addition to collecting information on individual healthcare utilisation and choice of provider for outpatient visits, the 2007 IFLS conducted surveys in health facilities to record their various characteristics including price of service, availability of various drugs and medicines, availability of various medical equipment, and number of health professionals working for the facility. Health facilities were randomly chosen in each community. Other characteristics of providers were obtained from community representatives, including information on distance from residential areas to health facilities. The data from health facilities and community representatives were then linked to individual data on healthcare utilisation and choice of providers. Consequently, no imputation on missing data is required, and the problem of selection bias is minimised.

As has been described briefly in Chapter 2, there are several estimation methods that can potentially be employed in evaluating the effects of provider characteristics, including nested logit, conditional logit and mix logit, also called RPL.[30] RPL offers relaxation of the IIA assumption, by allowing the coefficient of estimates to be random (McFadden and Train, 2000). In determinants analysis, this property is desirable if the effect of such characteristics is allowed to vary by individual. A study by Borah (2006), for example, found that healthcare providers located more than 10 kilometres away was undesirable for the majority of the population, but desirable for 21% of the population.

As it is reasonable to assume that individual preference to healthcare providers is not uniform across the population, RPL is an appropriate choice for assessing the effect of provider characteristics on choice of provider. RPL has been used widely in transportation research, primarily in studying discrete choice of transport mode (Hensher and Greene, 2003), and when complex calculations are needed. Only a few studies in healthcare utilisation have employed the RPL model thus far (Borah, 2006, Canaviri, 2007, Erlyana et al., 2011, Qian et al., 2009).

In a random utility theory, the utility of individual *i* from alternative *j* is set as:

$$\text{Prob}_{ij}(j|\Omega) = \int \frac{\exp(x_{ij}'\beta_i)}{\sum \exp(x_{ik}'\beta_i)} f(\beta_i|\Omega)\, d\beta_i \tag{6.1}$$

where β_i is the coefficient to be estimated, $f(\beta_i|\Omega)$ is the density of β_i, and Ω is the distribution vector of β_i. The parameter of the model can be estimated by maximum likelihood (Chang and Lusk, 2010). The coefficient of β_i can consist of random or non-random components, where

$$\beta_i = \begin{cases} b_1 + D\omega_i + \Gamma\eta_i \text{ if random} \\ b_2 \text{if non} - \text{random} \end{cases} \tag{6.2}$$

where b_1 and b_2 represent the average taste of responses or preferences in the population for the associated attributes, ω_i is vector of choice-invariant characteristics that generate endogeneity in the mean of β_i, D is the parameter matrix, η_i is the source of random variation and Γ is the non-correlated matrix (Borah, 2006).

[30] Terminology of mixlogit is used because the resulting estimation is a mixture of logit probability with specified mixing distribution (Borah, 2006). The term 'random parameter logit' is also commonly used, as it refers to the randomness of the estimated coefficient of the parameter. This study will use the term 'random-parameter logit' for consistency.

The dependent variable is type of healthcare provider; that is, traditional, public and private providers. Traditional providers such as *dukun* (traditional healers) and traditional midwives are also private entities. However, as they are not part of the formal healthcare system as recognised by the MoH, in this study, traditional providers are treated as a separate entity from private providers. Public providers consist of public hospitals, health centres and auxiliary health centres, and they are managed and primarily funded by central, provincial or district government. Private providers are privately operated and funded by individuals, not-for-profit organisations or private enterprises. They include private hospitals, clinics, physician practices and paramedics, midwives and nurses.

The random component independent variables (also often called alternative-specific or random variables) are direct cost (price of services), accessibility (travel distance) and quality of service (availability of essential drugs and medicines and the number of medical doctors in the facility). Another possible variable for inclusion is travel time. However, due to high colinearity with travel distance, travel time is excluded.

Chang and Lusk (2010) suggested that RPL is sensitive to specification and that achieving convergence is challenging. Therefore, the RPL model in this study is leanly specified by limiting its number of variables. In this model, four non-random components of independent variables (that is, variables that do not change their values with choice of provider, such as age, sex and often called individual specific or user's characteristics variables) are included in the model. These variables are introduced as the covariates in the model to detect the source of variability in the coefficient of estimates of provider characteristics (A more comprehensive user's characteristic roles in healthcare utilization have already been intensively discussed in Chapters 4 and 5).

Table 6.2 Description of the variables used in the random parameter logit model

Variable	Provider	Mean	Std. Dev.	Min	Max
Alternative-specific variables					
Choice of providers					
Type of healthcare provider chosen by users	Traditional	0.11	0.31	0	1
	Public	0.30	0.46	0	1
	Private	0.59	0.49	0	1
Price (Price of service in Rp '000)					
The average cost of registration, consultation, injection and basic medication	Traditional	51.15	58.63	0	405
	Public	2.73	2.23	0	18.33
	Private	25.12	10.17	11.15	68.82
Doctors (Number of medical doctors)					
The average number of medical doctors working in the healthcare facilities	Traditional	0.00	0.00	0	0
	Public	1.27	0.85	0	5.33
	Private	0.52	0.79	0	5.20
Drugs[31] (Availability of drugs)					
The average of the index of availability of 11 categories of essential drugs in the facility (1, 2, . . . ,11)	Traditional	0.06	0.23	0	2.00
	Public	6.68	1.26	3.67	10.67
	Private	0.44	0.98	0	7.20
Distance (Travel distance in km)					
The average of distance of health facilities from the centre point of the residential area	Traditional	3.89	4.05	0.13	27.34
	Public	10.80	9.99	0.01	104.15
	Private	8.75	8.49	0.66	76.33
Individual-specific variables					
Income (monthly income in Rp million) The average household expenditure per month adjusted with provincial consumer price index		2.22	2.28	0.07	29.20
Insured (Insurance subscription status) 1 if insured, 0 if not		.31	-	0	1
Severity of illness 1 if missing daily activity and have to stay in bed due to illness		0.66	-	0	1
Place of residence 0 if urban, 1 if rural		0.50	0.50	0	1
Number of sample (N)		**2,564**			

These covariates are health insurance subscription status, household income per capita (in rupiah per month, adjusted by provincial consumer price index), place of residence (urban or rural) and severity of illness. Health insurance status and household income may be sensitive to cost-related variables such as price of service. People may also

[31] The private practices of physicians, midwives and nurses also stock drugs that can be dispensed directly to outpatients. These include primarily basic medicines such as painkillers and ointments. In absence of the drugs needed by patients, these services also provide drug prescriptions to pharmacies.

respond differently by the severity of their illness. For example, a person that has been suffering from a prolonged illness may consider distance to health facilities to matter less in choosing the type of service (Borah, 2006). People from different places of residence (rural or urban) may also not have a homogeneous response to distance and travel costs. Several studies in Indonesia have developed two separate models for urban and rural populations, based on the premise that health services in urban and rural areas are fundamentally different (Erlyana et al., 2011, Lance, 2003). In this model, the place of residence (rural and urban) variable is introduced to explore possible differences between the responses of urban and rural dwellers to various provider characteristics.

D. Result and Discussions

In the model estimation, a simulated maximum likelihood method was used by running 500 Halton draws for each sampled individual. The model was estimated using NLOGIT 5.0, developed by Economic Software Inc. The reference value for the dependent variable was traditional provider. Therefore, each estimated coefficient in this model is relative to traditional provider. Table 6.3 provides the estimation of the RPL model.

Table 6.3 Random parameter logit estimates

Variable	Mean coefficient	Standard error	P>z
A. Random variables			
Price	-0.018100 ***	0.004461	0.0001
Distance	0.146665 ***	0.032206	0.0002
Doctors	1.868851 ***	0.406537	0.0000
Drug	-0.560102 ***	0.113493	0.0000
B. Standard deviation of parameter distribution			
Price	0.007834	0.006392	0.1182
Distance	0.081269 ***	0.019371	0.0002
Doctors	1.316148 ***	0.250945	0.0000
Drug	0.989279 ***	0.128797	0.0000

C. Distribution of the coefficient	**Proportion of sample by preference (%)** Dislike	Like
Price	99.0	1.0
Distance	3.6	96.4
Doctors	7.8	92.2
Drug	71.4	28.6

N=2563; Log likelihood function = -2505.268; McFadden Pseudo R-squared =.1102641
Probability [Chi-squared > value] = .000
Notes: ***=significance at 0.001; **=significance at 0.01; *=significance at 0.05

All random variables that are related to provider characteristics have a significant influence on choice of provider. Price of service and number of doctors had an expected sign: people are more likely to choose less costly providers and those with a greater number of doctors. Distance from residential area to healthcare provider location was also an important factor in the choice of healthcare provider. However, the sign is opposite to expectations. People are more likely to visit healthcare providers located further away from residential areas. Drug availability is also important, but also opposite to the expected sign.

Different from other discrete models such as multinomial, nested and conditional logit, the RPL model is able to estimate the distribution of the coefficient of independent variables by assigning a distribution function to random variables. In other words, it can predict the proportion of the population on either side of the average values, or on either side of zero coefficients. The term that is usually used is 'dislike' for negative coefficients and 'like' for positive coefficients (Train, 1998).

In this model, the estimated individual coefficients are assumed normally distributed. Once the standard deviations of the coefficients are estimated, a t-test is conducted to evaluate their significance, and the proportion of the population with 'like' and 'dislike' preference to provider characteristics can be calculated (see Table 6.3). The negative sign in the mean coefficient implies that on average people dislike higher prices of service. In addition, the RPL model provides the standard deviation of the mean coefficient. Similar calculations are also conducted for individual specific variables (place of residence, income, severity of illness and insured), to evaluate the interaction effect between individual-specific and provider-specific variables (see Table 6.4).

In addition to four random variables specific to providers, the four covariates in the model are specific to individual users rather than providers. Adding covariates is essentially introducing an interaction between provider characteristics and user characteristics. According to Hensher (2003), significant interactions imply that there is a heterogeneity surrounding the mean parameter of the estimate. The absence of interaction, however, does not imply the absence of heterogeneity, but simply that the model failed to reveal its presence. In such situations, the analysis relies on the deviation of the parameter of estimates as the source of unobserved heterogeneity.

Table 6.4 Heterogeneity of mean parameters and distribution of the estimated preference of users to provider characteristics

Provider characteristics	Users characteristics	Heterogeneity		Distribution of sample by preferences (%)	
		Coefficient	SE	Dislike	Like
Price	Rural	0.017093 ***	0.004303	88.9	11.1
	Income	0.000089	0.000702	98.9	1.1
	Severity of illness	-0.008467 **	0.003273	99.9	0.1
	Insured	-0.008001 *	0.003953	99.6	0.4
Distance	Rural	-0.029237 *	0.028329	5.2	94.8
	Income	-0.002044	0.004967	4.0	96.0
	Severity of illness	0.039677	0.025380	1.7	98.3
	Insured	-0.001010	0.289668	3.6	96.4
Doctor	Rural	0.181891	0.289668	6.8	93.2
	Income	0.053967	0.043171	6.5	93.5
	Severity of illness	0.029069	0.244569	7.6	92.4
	Insured	-0.191291	0.240950	8.5	91.5
Drug	Rural	-0.173555 *	0.074813	74.3	25.7
	Income	-0.098621 ***	0.019858	78.5	21.5
	Severity of illness	-0.103880	0.070223	73.7	26.3
	Insured	0.330583 ***	0.080285	67.8	32.2

N=2563; Log likelihood function = -2505.268; McFadden Pseudo R-squared =0.1102641
Probability [Chi-squared > value] = .000
Notes: ***=significance at 0.001; **=significance at 0.01; *=significance at 0.05

D.1. Price of Service

Price of service is the average basic cost of outpatient visit, consisting of registration, consultation, injection (if necessary) and price of medicine. Compared to private and traditional providers, the price of outpatient services in public health facilities is much cheaper (see Table 6.3). The price for traditional practice includes both hard currency and in-kind payment (the monetised value of which is estimated by the provider). The medicine in this category, such as painkillers, can be dispensed directly by the medical professional and is usually not expensive. For traditional providers, medicine includes all herbs and other traditional medicines.

Price of service is an important factor that influences the preferences of providers (see Table 6.3). The standard deviation for the mean coefficient of price is different from zero. This implies that the preference to price of providers is quite homogenous; that is, close to the mean coefficient values. Further analysis shows that the proportion of the population that dislike higher prices is 99%, while only 1% of the population like higher prices.

The role of price of service on healthcare utilisation and choice of provider is one area of research that has received much attention, with a number of large studies seeking the association between price and utilisation (Akin et al., 1986, Audibert et al., 2011, Gertler and Gaag, 1990). For the Indonesian context, previous studies show that the association between price of service and utilisation is significant in the negative direction (Chernichovsky and Meesook, 1986, Erlyana et al., 2011, Lance, 2003). Thus, the RPL model in this study supports and extends previous findings that high price of service is associated with lower healthcare utilisation. This study also reveals the distribution of the preference and can predict individual coefficients if needed.

RPL in this study also explores the interaction between provider and user characteristics by evaluating the heterogeneity of parameter estimates. The results are presented in Table 6.4. There is heterogeneity in the responses to price of service among the population. The sources of heterogeneity for price of service include place of residence severity of illness and health insurance subscription. The heterogeneity in the income level is not statistically significant; indicating that price of service is influential to the choice of provider at all income levels.

The positive sign for place of residence ($p<0.001$) implies that, compared to urban residents, rural residents regard price of service as less important. The negative signs for severity of illness and being insured, on the other hand, indicate that price of service is more important for patients with severe illness ($p<0.01$) and insured patients ($p<0.05$).

Price of service is an important attribute for patients in choosing a healthcare provider. Regardless of their income level, patients are more likely to choose a healthcare provider with lower price of service. However, rural residents regard price of service is less important in choosing a healthcare provider, than urban residents do. This difference indicates heterogeneity in the response to price of service by rural and urban residents. Rural residents consider price of service less important, but regards distance more important. This is shown by a positive heterogeneity coefficient of *rural* to *price* and negative heterogeneity *of rural* to *distance* in the model estimates. Thus, for rural residents, choosing a health provider which is closer to their home is more important, while choosing a provider with lower cost of is less important. This result is consistent with a study by Erlyana et al., (2011) using 2000 IFLS data. This indicates that from 2000 to 2007, the problem of distance in accessing health providers still persists in rural areas.

Due to the limitation of the information in the 2007 IFLS survey, further analysis of what the distance really means in relation to the choice of providers could not be tested. Several possible explanations can be offered to describe the roles distance in choice of health providers. Distance can be associated with travel cost or opportunity cost of seeking health care. In rural areas lack of transportation means and onerous journey may also prevent rural residents from accessing public providers which charge less medical fee. Erlyana et al. (2010) associated distance with travel cost for accessing access healthcare. Thus, it constitutes of non-medical cost. Jordan et al. (2004) indicates that distance may not reflect accessibility. In some regions, accessibility is better reflected by other measures such as availability of public transports (Lovett et al., 2002) or having driver's license (Arcury et al., 2005). The role of distance is discussed further in Section D.2 of this thesis.

Although it is not possible to completely isolate the effect of price of service from confounding factors such as limited availability of less-costly provider in rural areas, the inclusion of other provider characteristics in this model, i.e. travel distance, number of doctors and availability of drugs , as well as inclusion of user's characteristics such as income, severity of illness and insurance subscription status help in explaining how provider's and user's characteristics influence the choice of providers.

In addition, the sampling selection of facilities in 2007 IFLS is designed to reduce heterogeneity in the access to health facilities. The sample of health facility is randomly selected to represent each type of providers within each enumeration area. A facility is excluded if it was more than 45 minutes away by motorcycles. This will help in ensuring that the accessibility to all healthcare providers for patients both rural areas can be statistically compared to the accessibility for urban areas.

The more severe the illness, the more important the variable of price of service is to the preference of healthcare provider. There are two possible explanations for this. First, the more severe the illness, the more intensive and skilled is the medical care needed, which in turn is more costly. In this case, the price of service is important as patients can spend less money for the same level of quality. Second, the price of service is associated with the cost of medicine. Since more severe illnesses usually require intensive medicine use, the choice of provider is important to reduce the financial burden of medicine without sacrificing quality of service.

In this study, price of service matters more for insured patients than for uninsured patients. One possible reason for this is that some types of health insurance require co-payment, which constitutes an out of pocket expenditure for healthcare utilisation. In addition, higher price of service is more likely to be associated with technologically advanced treatment and more prescribed medicine which is costly and is not covered by the insurance. Sparrow (2010), for example, indicates that in urban areas, people with Askeskin insurance also had to bear part of the costs of extra public services. In addition, access barriers to health are not fully overcome by a health card as a mean of a user fee waiver because of direct and indirect costs of using the card, especially in remote and rural areas (Sparrow, 2008). It should be noted that due to difference in the benefit coverage, preferred providers and premium contribution, each type of insurance may have different effects on patient' preferences to price of service.

D.2. Distance

Distance is measured by average kilometres required to travel from a central point in the residential area to the location of the healthcare provider. The 2007 IFLS data shows that on average the travel distances to traditional, public and private providers are 3.9 kilometres, 10.8 kilometres and 8.7 kilometres, respectively. Although the closest, the utilisation of private providers is the lowest, at only 11% of total utilisation.

The RPL model estimates the mean coefficient of distance as statistically significant in the decision to choose a provider. The significance of distance, however, seems to be in the opposite direction. In this case, the farther away the location of the healthcare provider, the more likely people are to choose them for outpatient services. This counterintuitive result probably stems from the fact that people care less about distance travelled than they do about other characteristics, such as unobserved quality of services. Within the context of this study, people are willing to bypass traditional providers to choose public health centres or private providers that are farther away from their residential areas.

This bypassing phenomenon has been studied in several countries, including Tanzania (Kruk et al., 2009, Leonard et al., 2002) and Uganda (Parkhurst and Ssengooba, 2009). People bypass the nearest healthcare providers to seek care from a provider that offers higher quality. If quality is the cause of bypassing, however, a complication arises. First, the model assumes homogeneity in the quality of healthcare providers; that is, all healthcare providers with good and not good quality of service are homogenously distributed in the community. Second, measures of quality (including number of doctors and drug availability) have been included in the model. These two conditions are intended as controls preventing preference for distance being due to quality of service.

Therefore, the positive effects of distance may be influenced by other unobserved quality characteristics of healthcare providers, or by the individual characteristics of the users. A study in Sri Lanka shows that bypassing occurs as a response to variation in quality of care relative to price of service, and the more severely ill tend to bypass and travel further (Akin and Hutchinson, 1999). Similarly, in China, bypassing is more likely to occur among sicker patients or poorer patients (Audibert et al., 2011). The rate of distance also reduces utilisation level according to social economic variables and illness (Stock, 1983).

Another explanation is that spatial distance may not necessarily reflect accessibility. A study in rural West England (Jordan et al., 2004) showed that straight-line distance is not an accurate measure of access for peripheral and rural areas. Straight-line distance underestimates true travel distance, since road networks are sparser and other geographical barriers such as hills, rivers and coastline influence time spent travelling. Thus, driving time is judged to better reflect access to health services.

Jordan et al. (2004) further deemed drive time as potentially not applicable, because many sizeable households have no car. Therefore, he suggested that measures of geographical access should be made more accurate by integrating public and private transport availability with distance and travel time. A study on accessibility by bus to GPs in England (Lovett et al., 2002) showed an association between public transport and access to GPs. In rural California, in addition to distance, spatial behavioural factors such as having a driver's license and use of provided rides were significantly related to regular check-ups (Arcury et al., 2005).

The significant standard deviation of distance parameter distribution (see Table 6.3) suggests that there are significant variations in the preference to distance among the Indonesian population. These variations can be seen, among others, from the heterogeneity of the mean parameters by individual users' characteristics in Table 6.4. Heterogeneity exists from place of residence, showing that distance matters more for rural dwellers than it does for people living in urban areas ($p<0.05$). Heterogeneity effects are also found from household income, severity of illness and health insurance status, but these are not statistically significant.

The problem of distance was principally concentrated in rural areas. Table 6.5 shows that compared to traditional providers (as the reference in this model), distance to private and public healthcare providers in rural areas is farther than in urban areas. For urban residents, distance does not necessarily reflect difficulties in access to healthcare providers, since there are more options of transportation mode. For rural residents, due to lack of transportation modes, a small difference can greatly affect accessibility. In addition, geographical conditions in rural areas, especially in remote regions, make distance more problematic.

Table 6.5 Difference in the distance to healthcare providers from rural and urban residential areas

Type of healthcare provider	Average distance to healthcare provider(km)	
	Rural	Urban
Public health centre	14.6	7.7
Private healthcare provider	12.4	5.5
Traditional practitioner	4.7	3.0

Source: Calculated form 2007 IFLS

This finding is in accordance with studies on the effect of distance to healthcare utilisation. Various studies conducted in other countries with rural respondents have commonly found a negative association between distance and healthcare utilisation. This was the case in Kenya (Mwabu et al., 1993), rural India (Borah, 2006) rural China (Qian et al., 2009), West England (Jordan et al., 2004), rural California (Arcury et al., 2005) and rural Vermont (López-Cevallos and Chi, 2010). Distance has also been associated with the utilisation of other types of service, such as health services for asthma (Jones et al., 1998), inpatient services (Haynes et al., 1999) and cancer treatment services (Campbell et al., 2000).

D.3. Number of Medical Doctors

The number of medical doctors is one of the characteristics with a positive and significant influence on the decision to choose a provider. A healthcare provider with a greater number of doctors is preferred by the majority of the sample population (96.4%). This finding is consistent with a study on the number of medical doctors in rural China (Yip et al., 1998) and studies on the role of quality of service in general (Canaviri, 2007, Habtom and Ruys, 2007, Sahn et al., 2003).

Number of doctors is an instrument to produce quality healthcare (Donabedian, 1966, 1978). People prefer health facilities with more medical doctors, and equate this with the expectation of better treatment for their illness, even if they have to travel a longer distance to access the service. Several studies have shown that people bypass their nearest healthcare providers to improve the quality of care they receive (Klemick et al., 2009, Leonard et al., 2002).

The variation in the availability of medical doctors in health facilities can be observed in Table 6.2, especially between public and private providers. (By definition, traditional practices do not employ medical doctors in their facilities). On average, there are 1.27 medical doctors per public healthcare provider, with a minimum number of 0 and a maximum of 5.3. Although some public healthcare providers, such as health centres, do not have medical doctors, this is quite rare. A private provider, on the other hand, on average has only 0.52 medical doctors. In other words, one out of two private providers does not employ any medical doctors. If number of doctors indicates the quality of service, the higher standard deviation on number of medical doctors shows that the disparity in the quality of private providers is larger than in public providers.

A small percentage of the population (7.8%) prefers providers with fewer doctors. This preference is most likely related to the individual, social and cultural characteristics of the users, rather than to the characteristics of providers. All things (distance, cost and drug availability) being equal, preference towards traditional providers may be related to beliefs or cultural values that do not change easily with shifts in income, access to health insurance or other social economic circumstances. Susenas data from 1996 to 2009 shows that the proportion of the population choosing traditional practices declined only slightly (see Figure 3.9 in Chapter 3). Compared to visits to public and private facilities, the trend of visits to traditional practices is much more stable.

The role of number of medical doctors in choice of provider in this study is quite strong, regardless of the characteristics of the users. The heterogeneity in the preference for more medical doctors is insignificant across all groups; that is, urban or rural, all levels of household income, severity of illness and insured or uninsured.

D.4. Drug Availability

Drug availability is another variable to measure the quality of services. Various studies have been conducted to investigate the role of drug availability on healthcare utilisation. In Bolivia, the availability of drugs is significant in determining healthcare utilisation of private providers (Canaviri, 2007). A study by Leonard et al. (2002) suggested that patients seek facilities that provide high-quality prescriptions and that are better stocked with basic supplies, but that they avoid services that overprescribe medication. Other studies have found a positive association between drug availability and healthcare utilisation (Litvack and Bodart, 1993, Waddington and Enyimayew, 1989, Yoder, 1989). Yet others have found that the association is insignificant (Sahn et al., 2003).

In this study, drug availability is associated with healthcare provider choice. However, the sign of the coefficient is opposite to expectations. On average, people are more likely to choose healthcare providers with less availability of drugs. Although better drug availability deters patients from choosing a provider, the standard deviation is quite large and significant. This means that a significant proportion of the population prefers better drug availability. As shown in Table 6.3, 71.4% of Indonesian patients dislike and 28.6% like health facilities with better drug availability.

Drug availability can be viewed as an instrument of quality medical care (Donabedian, 2005, 1978, 1966). Drug availability is an observed quality of care, referring to the structure and process of standard of care and to whether this standard is met. Perceived quality, on the other hand, refers to the view of the patients (Donabedian, 1980, Palmer et al., 1991). In this study, the quality-related variable is clearly related to observed, rather than perceived, quality. Observed provider characterises can be translated differently by different patients, such that patients do not always choose visibly better quality providers.

This can be observed from the significant heterogeneity in the responses to drug availability based on the different characteristic of the users. Drug availability was more important among rural residents, those with higher household income levels and for those with severe illness or subscriptions to insurance. Heterogeneity from individual characteristics helps in explaining the negative effects of drug availability on choice of providers.

Drug availability can also be viewed from the perspective of potential escalations in the cost of prescribed drugs, and over prescription. A study in Tanzania found that although patients preferred health facilities with better drug availability; over prescription deterred them from choosing certain facilities (Leonard et al., 2002). In Indonesia, there is an indication that unaffordable charges for medicine deter patients from utilising health facilities (Hawkins, 2009).

In this study, price of service does not include the charge for prescribed medicine. When patients consult medical professionals, they are often prescribed with a list of medicine that can be bought from pharmacies, provided by the health facility or procured elsewhere. Private physicians, especially in rural and remote areas, usually also provide prescribed medicine which are charged to the patients on top of price of service.
As these pharmacies have an incentive to keep price high, the cost of medicine is high. According to the National Institute for Health Research and Development Centre (NHRDC), in 2004, the price ratio to median international indicator price of private pharmacies and public hospitals was 22 to 26 for originator brands, 1.7 to 7 for most generic brands and 2.15 to 2.6 for the cheapest generic medicines (Hawkins, 2009).

Higher price of medicine at health facilities and weak law enforcement leads to high rates of illegal sales of prescription drugs by unlicensed outlets, doctors and other health workers. It is estimated that in 2004, there were some 5,000 unlicensed drug stores and some 90,000 small stores and peddlers (Hawkins, 2009). Easy and less expensive access to medicines other than from health facilities, especially in urban areas, can further explain the negative association between drug availability and choice of provider. In rural areas, where medicine is more difficult to get from stores, vendors and peddlers, patients have to rely on health facilities to access medicine. As a result, to rural residents, drug availability in health facilities is more important. This is shown in the model in the significant coefficient of heterogeneity in the mean parameter (see Table 6.4).

D.5. Methodology Considerations

The RPL model in this study seeks associations between provider characteristics and the use of three types of healthcare provider: traditional, public and private. This categorisation was based on the nature of provider management and ownership, and was commonly used in the studies of healthcare utilisation. The caveat of this categorisation is reduction of variability in the information of provider characteristics due to aggregation. For example, public providers are an aggregation of health centres and public hospitals, which have a distinct number of medical doctors and price of service, as well as distance. Similarly, private providers consist of private GPs, midwives, clinics and hospitals, each of which has distinct characteristics.

Analysis in a lower hierarchy of healthcare providers would possibly yield a higher variation and a greater accuracy of estimates. However, aggregation is unavoidable as data on providers are not available beyond traditional, public and private categorisations. Further, traditional, public and private categorisations of healthcare providers are a natural occurrence in the public policy narrative. Various healthcare policies are driven by this categorisation, such as preferred provider of health insurance, pharmaceutical scheme subsidies and targeted populations. Most previous studies on the roles of provider characteristic also use similar aggregations in their models.

The RPL model used in this study is an attempt to capture the various providers' characteristics that are theoretically influential to the decision of choice of provider. In addition to price of service, travel distance, numbers of doctors and drug availability, other characteristics that are found to be important are travel time (Habtom and Ruys, 2007, Leonard et al., 2002), travel cost (Wiseman et al., 2008), qualification of medical professionals (Klemick et al., 2009) and indirect cost of service (Habtom and Ruys, 2007).

Inclusion of these variables could provide a more elaborative interpretation on the choice of provider. The economic concept of opportunity cost, for example, could give more understanding on the roles of distance. In this study, distance reflects the degree of geographical barrier to access. From an economic perspective, it reflects the opportunity cost or indirect cost of service (Folland et al., 2012). Distance indicates the time a person is willing to give up seeking medical care, which is specific to individual circumstances. A user with a good job and high salary may interpret distance (and waiting time in health facilities) as the wage lost due to seeking healthcare. On the other hand, a person who is not in employment gives less value to distance, since their forgone earnings due to seeking care are negligible.

Although RPL is considered the most promising model in multinomial choice, and as appropriate for use in studying various aspects of behaviour, a model is only as good as the data from which it is estimated (Hensher and Greene, 2003). The stability of estimates is of concern among researchers, and hence maintaining a large sample size is important to produce precise estimates (Chang and Lusk, 2010, Hensher and Greene, 2003).

Due to limitations in the data and concerns about maintaining the stability of the estimates, only the four provider characteristics discussed in detail above are included in this model. These variables are intended to represent the dimensions of affordability (price of service), accessibility (distance) and quality (number of doctors and drug availability) of providers as comprehensively as possible. Further study to investigate other characteristics is suggested whenever data is available.

Overall, the use of RPL offers significant contributions to the area of healthcare utilisation research. First, it avoids the IIA assumption, which is not appealing in the study of consumer behaviour (Greene and Zhang, 2003) but which is commonly found in discrete choice models (McFadden and Train, 2000, McFadden, 1986). Second, it can explore deeper into variations of consumer response, which are otherwise assumed as constant in other statistical models (Hensher and Greene, 2003, Train, 1998). For example, in this study, the RPL model reveals that drug availability is preferred by 28.6% of patients, but disliked by 71.4% of the population.

E. Summary

The notion that provider characteristics exert a significant influence on healthcare utilisation has existed in Indonesia for some time. In an attempt to reduce the financial barriers to health services, government has provided subsidies to health facilities and introduced a health insurance scheme for the poor and near poor. However, studies on the roles of provider characteristics based on empirical data have been lacking. This study is an attempt to explore the relationship of provider characteristics in healthcare utilisation and their interaction with individual users' characteristics.

Using an RPL model, four provider characteristic variables (price of service, travel distance, number doctors and drug availability) and their interaction with user characteristics (place of residence, income level, health insurance subscription and severity of illness) are examined.

The results show that price of service and number of doctors has a significant influence on the choice of provider. On average, a high price of service and high number of doctors in health facilities are associated with more healthcare utilisation. This finding is consistent with previous studies on healthcare utilisation, both in Indonesia and in the international context. The negative association of price and utilisation is explainable by an economic principle; that is, all other things being equal, people try to maximise their utility with as few resources as possible. Further, as number of doctors reflects quality of service, patients prefer facilities with a higher number of doctors to treat their sickness.

Travel distance and drug availability also have significant associations with healthcare utilisation, but with the opposite to expected sign. People seem to prefer longer distances and less drug availability. By examining previous studies from elsewhere and investigating the health system context in Indonesia, this counterintuitive result can be explained. People are willing to travel more and bypass the nearest healthcare provider in search of less expensive or better quality health services. As drug availability is often associated with the higher cost of medicine or over prescription, patients compromise by choosing facilities with lower drug availability. In addition, drug availability as an observed provider quality standard does not necessarily reflect the level of quality as perceived by users.

From the RPL model, it is also observed that the preference for such provider characteristics is not uniform. There is considerable variation in preferences among the population (with the exception of for price of service, which does not deviate significantly from the mean). Some people like certain provider characteristics, whereas others dislike the same. These variations are also determined by individual user characteristic. In other words, there is an interaction between the effects of provider characteristics and the characteristics of the users.

Although RPL can provide information on the effects of provider characteristics and their interaction, the model is limited by the existing categorisation of healthcare providers. Further, many questions remain unanswered with this model and require further investigation with more extensive variables if possible.

Chapter 7
Indonesian Population 2010–2025

This chapter describes the dynamics of the demographic characteristics of the Indonesian population, with an emphasis on the recent and projected population in the next 15 years. The content is not limited to an examination of demographic components, but also touches upon relevant social economic characteristics, the current epidemiological situation in Indonesia and the overall objectives of national economic development. The analysis from various perspectives on the future population of Indonesia lays the foundation for the projection of demand for healthcare in the future that will be presented in Chapter 8.

The chapter starts with an overview of the population dynamics in Indonesia, including the current population size and structure, distribution and growth. After that, a review of the population projection methodology will be presented, followed by discussion on the assumptions (fertility, mortality, migration) used in the projection. Finally, the result of the population projection and overall social economic characteristics and epidemiology will be presented.

A. Indonesian Population Dynamics

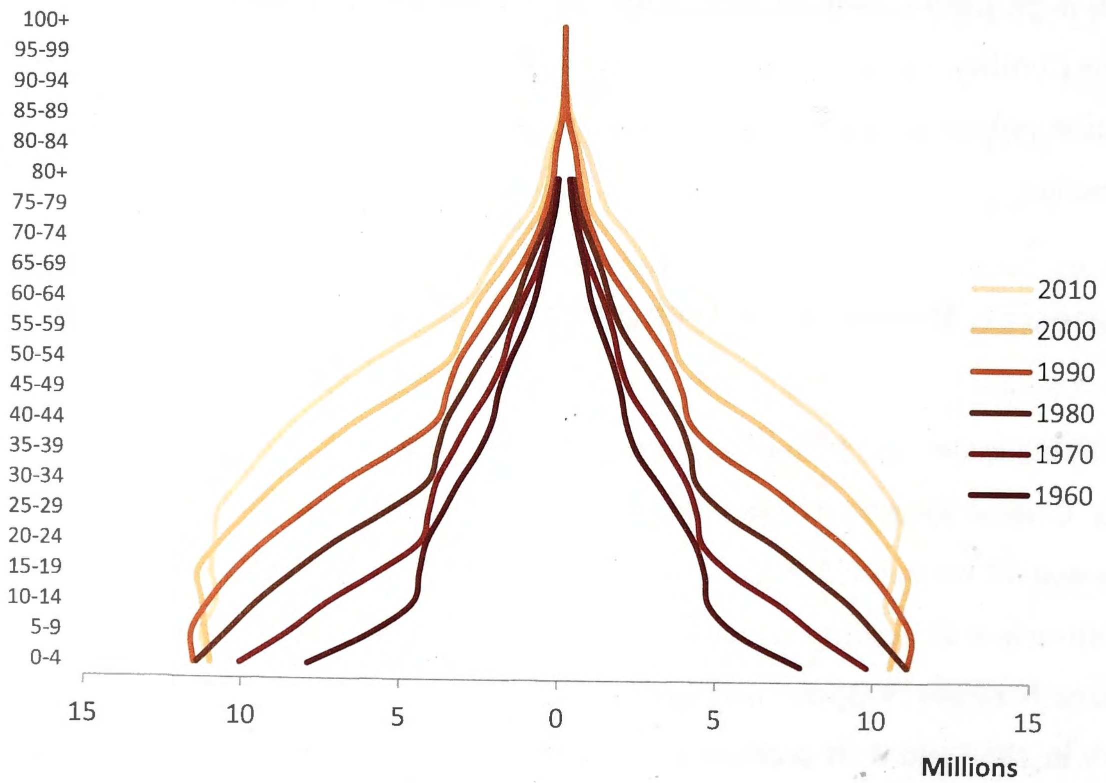
In the last five decades, the Indonesian population has grown substantially. In 1960, the Indonesian Central Board of Statistics (ICBS) official estimate of the Indonesian population was 97 million (McNicoll and Mamas, 1973). There has been some dispute over the estimation of fertility rates (Iskandar, 1970, Keyfitz, 1965, Nitisastro, 2006). McNicoll and Mamas (1973) claimed that total fertility rate (TFR) increased from 4.7 in 1963 to 5.9 in 1967 and then declined to 5.0 in 1970. The IMR continued to decline to 143 per 1,000 live births between 1960 and 1970 (McNicoll and Mamas, 1973). Improved sanitation, access to food, healthcare and overall economic development enabled the population to grow to 119.2 million in 1970 and 214.6 million in 2000.

Between 2000 and 2010, the population grew 1.4% annually to 249.8 million, making Indonesia the fourth most populous nation in the world.

Even though the size of the population continues to grow, the growth rate is declining. Between 1971 and 1980, the average annual growth rate was 2.30%, and this has since declined to 1.97% between 1980 and 1990 and 1.70% between 1990 and 2000. In the last decade, the average annual growth rate was 1.49%. In 2010, more than one-half of the population lived on Java Island, although its area is only 7% of the nation's land. The TFR for Java is relatively low. As a result, the population of Java has grown more slowly than in other regions. In 1960, 65% of the population lived on Java. This proportion declined to 64% in 1971.

The Indonesian population has been urbanised, either by people moving into cities, or because areas have been reclassified as urban. In 1960, the urban population accounted for only 15% of the total population. By 2010, this had increased sharply to 50%, and urbanisation is expected to reach 72% by 2050 (United Nations, 2011).

Figure 7.1 Indonesian population pyramid 1960–2010

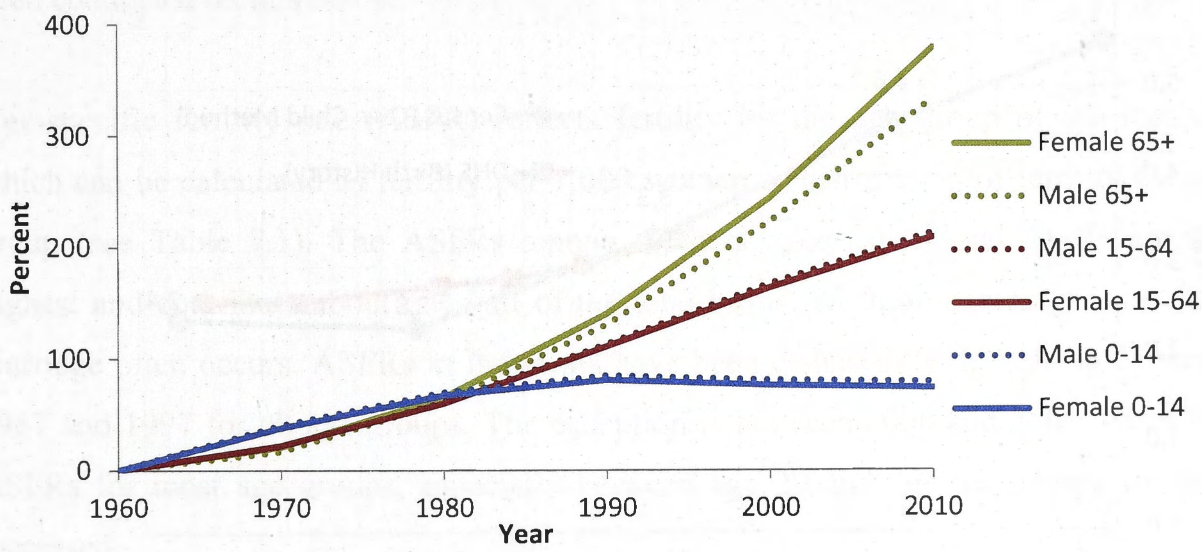


Data source: UN Population Prospect 2010 revision

In 1960, children comprised the most significant proportion of the population; and until 1990, this younger cohort was still growing. After the 1990s, however, with the decline in fertility, number of births stabilised and then began to decline. Combined with a decline in the overall mortality rate, the population structure has started to shift from predominately young to a period of an ageing population.

The pattern of ageing can be observed from the high growth of the elderly and adult cohorts. Between 1990 and 2010, the elderly population increased 333% for males and 379% for females. In terms of proportion to total population, the share of the elderly (65+) population grew from 3.6% in 1960 to 6.4% in 2010. Figure 7.2 shows this increase (%) graphically for each age bracket by sex, depicting the large increase in the elderly population.

Figure 7.2 The Change in size of population 1960–2010 (1960 as the baseline), by age group and sex

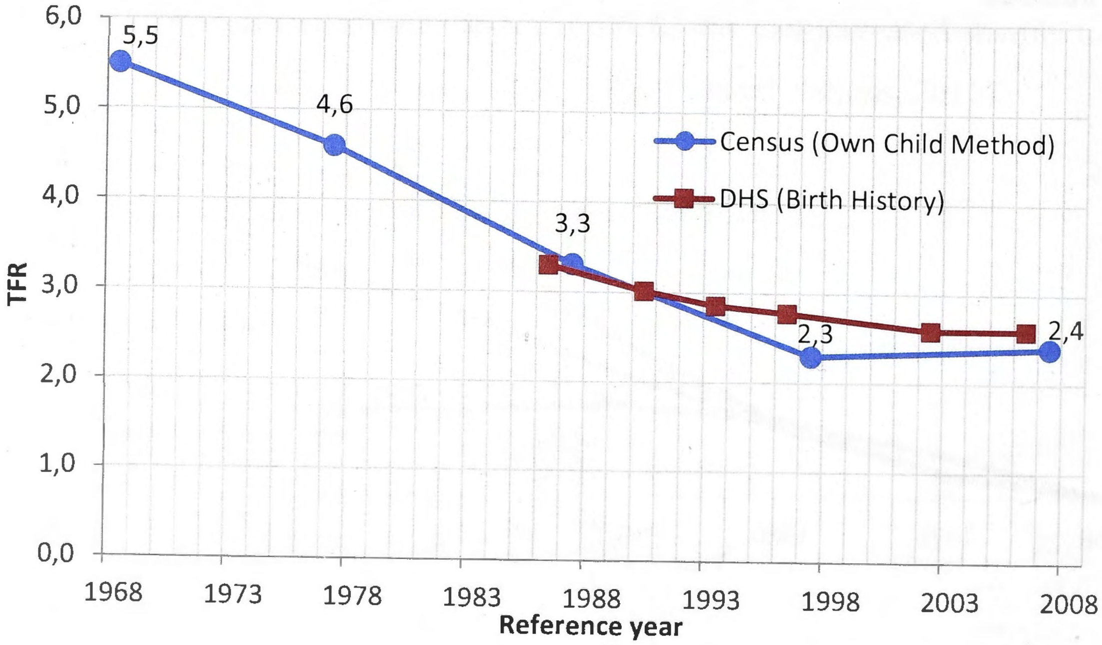


To compare internationally, the extent of ageing in Indonesia is quite moderate. Thus, even though the population is aging substantially, relative to total population, this increase is relatively small. One of the reasons is that the population aged 15–64 (often referred to as the economically active population) is also growing. Between 1960 and 2010, for example, this segment of the population grew from 56% to 67% of the total population. As a result, Indonesia's old-age dependency ratio (ratio of population aged 65+ per 100 population aged 15–64) increased only slightly, from 6.3% in 1960 to 8.2% in 2010 (United Nations, 2011).

A.1. Fertility

In the last decade, the fertility rate has dropped by about 50%, from 5.6 children per woman in 1967–1970 to 2.4 in 1967–2000. Regionally, the decline in fertility has been greater for Java than for other regions. Different from the western world, where early fertility decline was due to natural contraception methods and less support from the government, in Indonesia the decline is primarily attributed to family planning (Adioetomo et al., 1989, Gertler and Molyneaux, 1994, Hugo et al., 1987, McNicoll and Singarimbun, 1983) and systematic basic social and economic institutionalism (Hull, 1987). Referring to Bongaarts and Potter (1983), all four approximate determinants of fertility (age at first marriage, contraceptive use, breastfeeding and abortion) have effects on the reduction of fertility in Indonesia (Muhidin, 2002).

Figure 7.3 Trend of TFR in Indonesia[32]



Data sources: Population census and IDHS, various years.

The most current census (2010) indicates that the TFR increased to 2.4 in 2006–2010. There has been speculation on what led to this increase in fertility and what the consequences are. For example, some government officials believe that the increase in fertility indicates a weakening in the family planning program, which, since 2001, has been decentralised. Many demographers, however, suggest that the increased TFR in the most current census can be explained by other factors. From a measurement perspective,

[32] The TFR is calculated for four-year-periods prior to the census or survey. On the graph, the TFR rate is placed at the middle year of the estimated period. For example, the 2010 census estimated a TFR of 2.4 between 2006 and 2010. On the graph, this rate is represented as a point in year 2008

the increased TFR is anticipated and falls within some likely scenarios in the UN Population Projection (United Nations, 2011). Since no civil registration data exists, it is difficult to compare the reliability of measurement of fertility in a census. The census's own child method may suffer from underreporting by single women and changes in coding methodology by statistics officers. The IDHS birth history method has also been reported to overestimate TFR due to missing information on single women (Hull and Hartanto, 2009).

The census enumeration quality may also contribute to the sudden increase in the TFR. The coverage, use of invented data verification methodology and ample support from the government has led the 2010 census to be regarded as the most elaborate and successful population census in Indonesian history (Hull, 2010). If this is the case, it is possible that the 2000 census, in fact, is the one that underestimated TFR. A further possibility is the presence of the tempo effect of fertility, even though no research has been conducted on this matter.

Age-specific fertility rate (ASFR) reflects fertility by the age group of the mother, which can be calculated as fertility per 1,000 women or distribution of fertility by age group (see Table 7.1). The ASFRs among mothers aged 20–24 and 25–29 are the highest and contribute about one-half of the total births. At these age ranges, the first marriage often occurs. ASFRs in Indonesia have been consistently decreasing between 1967 and 1997 for all age groups. The exception is between 2006 and 2009, when the ASFRs for most age groups, especially between age 20 and age 39, appear to have increased.

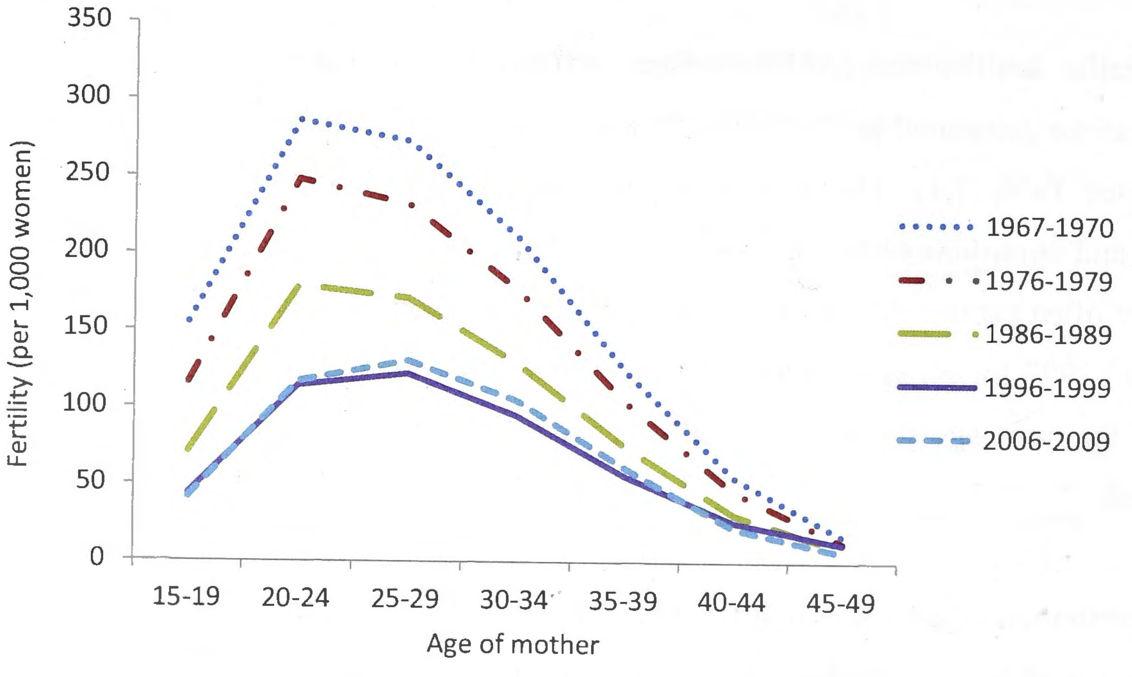
The contribution of each group to fertility also changes across time. Over the years, the contribution of younger women has decreased, while the contribution of older women has increased. For example, the contribution of the 15–19 age group to fertility during 1967–1970 was 14%. Five decades later, this contribution had decreased to 9%. Over time, the biggest contributor to overall fertility has shifted from the 20–24 age group to the 25–29 age group.

Table 7.1 The age specific fertility rate and proportion of fertility in Indonesia 1960–2010

Period	Year of reference	15-19	20-24	25-29	30-34	35-39	40-44	45-49	TFR
		Age of woman							
Fertility per 1,000 women									
1967–1970	1968	155	286	273	211	124	55	17	5.5
1976–1979	1977	116	248	232	177	104	46	13	4.6
1986–1989	1987	71	179	171	129	75	31	9	3.3
1996–1999	1997	44	114	122	95	56	26	12	2.3
2006–2009	2007	41	117	130	104	61	22	6	2.4
Percentage distribution									
1967–1970	1968	14	26	24	19	11	5	2	5.5
1976–1979	1977	12	26	25	19	11	5	1	4.6
1986–1989	1987	11	27	26	19	11	5	1	3.3
1996–1999	1997	9	24	26	20	12	6	3	2.3
2006–2009	2007	9	24	27	22	13	5	1	2.4

Data source: Population Census 1970, 1980, 1990, 2000 and 2010

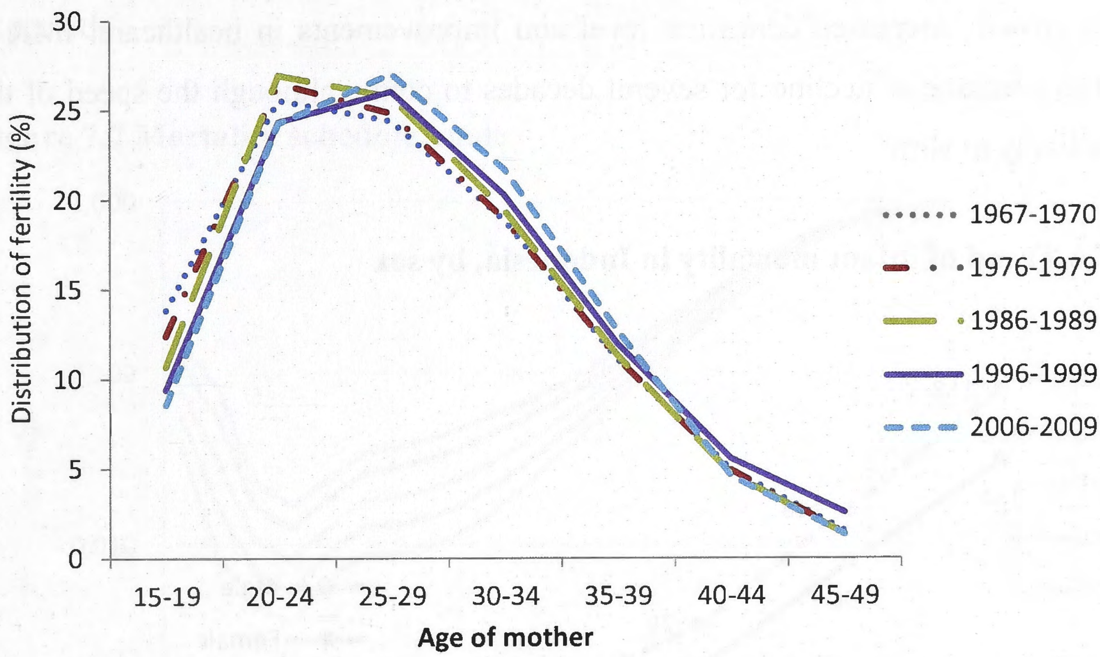
Figure 7.4 Age-specific fertility rates, Indonesia 1960–2010



Data source: Population Census 1970, 1980, 1990, 2000 and 2010

The reduction of fertility at all levels and the shift of fertility from younger to older cohorts may indicate the presence of a tempo effect caused by the delay of births to older ages. Muhidin (2002) indicates that the tempo effect can be observed in fertility estimates using IDHS data. The peak of fertility rate has shifted from women aged 24 years in 1998–1991 to women aged 26 years in 1992–1994. Figure 7.4 shows the ASFRs calculated from the 1970, 1980, 1990, 2000 and 2010 census. In the last two population censuses, the fertility peak has shifted from mothers aged 20–24 to mothers aged 25–29.

Figure 7.5 Percentage distribution of fertility, Indonesia 1960–2010



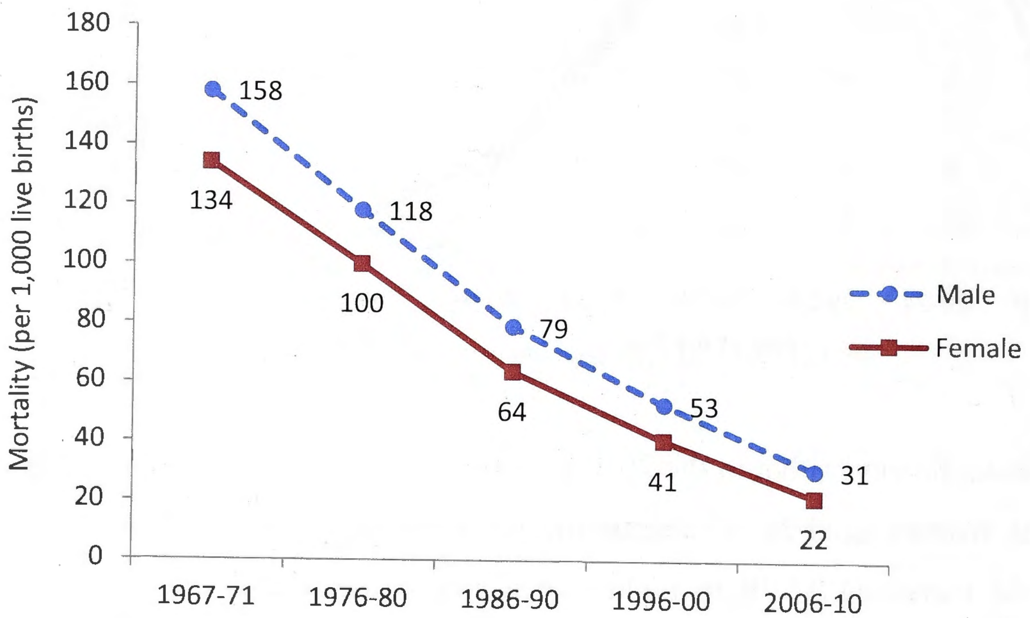
It important to note, however, that in the 2010 population census, the TFR was recorded to increase, with women aged 25–40 accounting for much of this trend. Thus, it is not clear whether the increased ASFR in middle-aged women represents delayed fertility (tempo effect) or an increase in total fertility (quantum effect).

A.2. Mortality

Information on mortality in Indonesia is not available from civil registration, and therefore is estimated directly or indirectly from censuses or surveys. Even so, most of the data available are on infant and child mortality. Infant mortality has been estimated using various methods such as the Brass and the Brass-Trussell methods from population censuses. The IDHS provides full birth history for direct infant mortality estimates. However, the estimates are limited to the national level, due to the limited number of the sample.

Census data shows that IMR in Indonesia has declined quite sharply. In the 1960 Census, estimated IMR (number of infant deaths per 1,000 live births) was 158 for males and 134 for females. This figure dropped to 31 and 22 for males and females, respectively, in the 2010 census (see Figure 7.6). Estimates of IMR from IDHS data are lower than from the census, but they show a similar dramatic decline. With the current trend of IMR, Indonesia will likely achieve its 2015 MDG target of IMR (males + females) at 23 deaths per 1,000 live births (Bahjuri-Ali et al., 2009). With the current economic growth, increased education level and improvements in healthcare, IMR is expected to continue to decline for several decades to come, although the speed of the decline is likely to slow.

Figure 7.6 Trend of infant mortality in Indonesia, by sex

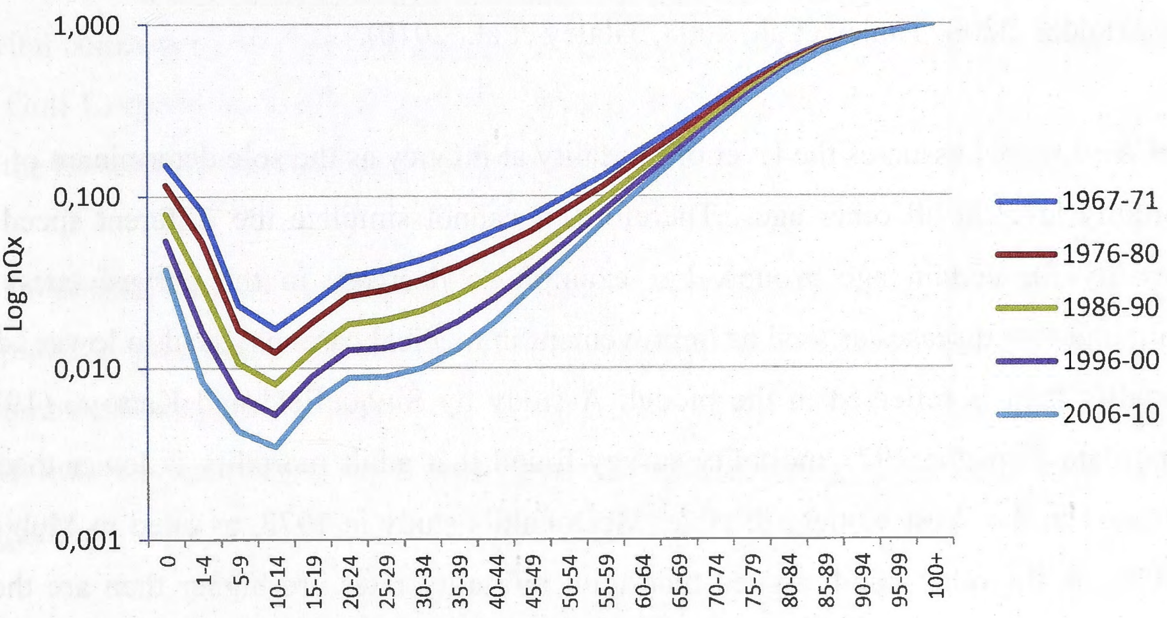


Data source: Population census, various years

Data on adult mortality rate in Indonesia are more difficult to obtain, even at the national level. Prior to 2010, no large-scale survey or civil registration recorded information on adult mortality. As a result, information on mortality schedules is usually borrowed from a model life table. The most commonly used model life tables are the West model of Coale-Demeney and the UN General model life table (Nitisastro, 2006). Using the West model life table is simple as it requires only one parameter (IMR), and it is thus probably more parsimonious than are other methods that require more parameters. The West model is very useful and widely used in countries in which empirical data on mortality is limited. There have also been attempts to use the Heligman-Pollard (Iskandar, 1970) and National Social and Economic Survey and National Household Health Survey (Iskandar, 1970, Muhidin, 2002).

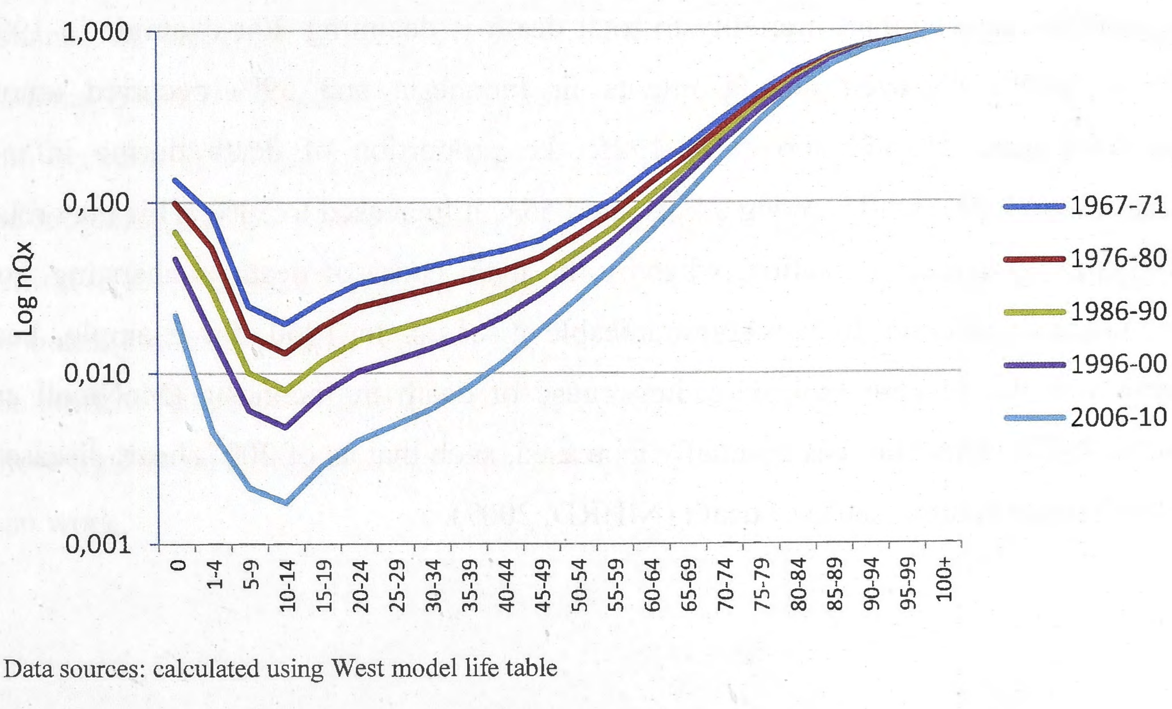
Figure 7.7 shows the mortality patterns derived from information on IMR from the 1971, 1980, 1990, 2000 and 2010 censuses, using the West model. It indicates that in the last four decades, overall mortality has decreased. Since this mortality schedule is derived from infant mortality, the downward shift of mortality at all age groups is expected.

Figure 7.7 Mortality schedule, male



Data sources: calculated using West model life table

Figure 7.8 Adult mortality schedule, female



Data sources: calculated using West model life table

The decrease in adult mortality is also evidenced by different methods of estimation such as census survival rate (Heligman and Pollard, 1980) and direct calculation of the

National Household and Health Survey (SKRT) 1991–1995 (Muhidin, 2002). The UN Population prospect estimated a reduction in the annual crude death rate (CDR) from 19 per 1,000 population in 1960–1965 to seven per 1,000 population in 2005–2010 (United Nations, 2011). This decrease in mortality has been partly attributed to extensive health programs triggered by the Health for All program (HFA) such as the implementation of the Alma Ata declaration of 1979 (Lieberman and Marzoeki, 2002). Public health interventions have also been able to reduce neonatal mortality significantly (Bhutta and Azra Haider, 2008, Titaley et al., 2008, Titaley et al., 2010).

The West model assumes the level of mortality at infancy as the sole determinant of the mortality level at all other ages. Therefore, it cannot simulate the different speed of mortality for certain age groups. For example, a decrease in the pervasiveness of communicable diseases as well as improvement in medical care may lead to lower adult mortality than is reflected in the model. A study by Sinquefield and Kartoyo (1977) using data from the 1973 mortality survey found that adult mortality is lower than is indicated in the West model life table. McDonald's study in 1978, as cited in Muhidin (2002), on the other hand, argued that adult mortality rates are higher than are those indicated in the model life table. Iskandar (1970) also found that the Indonesian pattern of adult mortality is different to model estimates.

The contribution of infant mortality to total death is declining. For example in 1992, 23% of deaths occurred among infants in Indonesia and 39% occurred among individuals aged 55 and above. In 1995, the proportion of death during infancy decreased to 12.9%, while among adults aged 55+, it increased to 53%. This may relate to the epidemiological transition, whereby the main cause of death is changing from communicable diseases to non-communicable diseases. In 1960, for example, heart disease was the seventh ranked leading cause of death in Indonesia (McNicoll and Mamas, 1973). This rank has gradually increased, such that as of 2007, heart disease is the first ranked leading cause of death (NIHRD, 2007).

A.3. Migration

The role of migration has long been recognised as a factor affecting changes in population. In many countries with a TFR below replacement level, migration relieves the overall lack of labour force and can be an important part of population growth and in the growth of the labour force (Edmonston and Michalowski, 2004). In Australia, for example, migration accounts for about two-thirds of national population growth, and is a vital component to offset the ageing population (McDonald and Kippen, 1999, 2011). In Gulf Corporation Council countries such as Bahrain, Qatar, UAE and Kuwait, 67% of the labour force comes from migration (Shah, 2012).

In Indonesia, data on international migration[33] is too patchy to be incorporated into a population projection. All of the existing population projections assume a zero net international migration, mainly due to this lack of data. However, this does not mean that international migration is negligible, as indicated by some scattered data of migration.

Data of the Directorate General of Immigration, Republic Indonesia, for example, shows that the trend in the number of passports issued has increased from 2.4 million in 2010 to 2.6 million in 2011 (Department of Law and Human Rights, 2011), although the issuance of passports is not necessarily linked to outmigration. Records from the National Board for Placement and Protection of Indonesian Workers (BNP2TKI) show that, between 2006 and 2012, about 4.0 million workers (mostly low-skilled workers, and including 3 million women) out-migrated to more than 50 countries, with about 2.8 million of these going to work in informal sectors. The two biggest destination countries for outmigration are Saudi Arabia (1.4 million) and Malaysia (1.1 million). Offsetting this outflow, workers returning home during this same period totalled about 2.8 million. These figures are certainly underestimated, since migration also occurs for reasons other than work.

[33] In this study, the unit of analysis is the national level. Therefore, internal migration will not be discussed, as it has no or little influence on the national change in the population.

Table 7.2 Number of Indonesian in- and out-migrant workers 2006–2011, recorded by BNP2TKI

	In	Out	Net (In-Out)
2006	376,782	680,000	- 303,218
2007	354,921	696,746	- 341,825
2008	447,016	644,731	- 197,715
2009	492,073	632,172	- 140,099
2010	466,491	575,803	- 109,312
2011	494,212	581,081	- 86,869
2006–2011	2,631,495	3,810,533	- 1,179,038

Source: BNP2TKI reports of 2006–2012 placements of workers

The UN Population Prospects 2010 revision estimates that during 2005–2010 in Indonesia 1.3 million net migration was inputted to the model for projection, an increase from 0.78 million a decade earlier (1995–2000). This estimate is close to the figure of net migration of legal workers recorded by BNP2TKI between 2006 and 2011.

B. Methods of Population Projections

There are various groupings of population projection[34] methods. George et al. (2004) differentiates subjective and objective projections. In subjective projections, data, techniques and assumptions are not clearly defined, such that the projections cannot be replicated accurately. Objective projections fall into three categories: trend extrapolations, cohort component methods and structural models (George et al., 2004, Smith et al., 2001). Trend extrapolations are based solely on past trends and they thus assume that future population is a function of time. The cohort component method projects population by three components of demography: fertility, mortality and migration. Structural models seek associations between demographic and other factors, such as income and land use, and predict future population based on changes in these factors.

These classifications are not always clear, and often they are complimentary (Booth, 2006). For example, objective extrapolations may incorporate expert judgment. If the details of components of demographics are needed for future population, the cohort

[34] Throughout this thesis, projection is differentiated from forecasting, although the distinction is not always clear. Projection is based on a particular set of assumptions regarding future populations. Forecasting is a projection based on the most likely prediction of the future (George et al., 2004).

component method is the one that is commonly used, although fertility, mortality and migration can be estimated using extrapolation and expectation (subjective methods).

Options for population projection methods in Indonesia are more limited. Historical data are only available consistently a few points back in time, and these are mostly based on seven decennial censuses and several inter-census surveys. Hence, time series can be used in the projection, but its accuracy may be subject to unstable fluctuation. In this case, subjective judgment by experts may be needed. Elsewhere, deriving targets of fertility by a group of experts has been used (Lutz et al., 1998, Lutz et al., 2001).

In this study, a cohort component method is used to project future population because details of demographic components are needed to project demand for healthcare. However, as indicated by Booth (2006), each component of demography may need some sort of extrapolation and subjective judgment. The next section will explore the base population cohort and projection of each demography component. Methods for migration projection, however, will not be explored, since net international migration in this study will be assumed as zero.

B.1. Base Population

The projection in this study will use the population cohort from the 2010 census, adjusted with the census Post Enumeration Survey (PES). Total Indonesian population in mid-2010, according to census data, was 237.6 million. The PES estimated that the census has undercounted by 8,317,446 people (3.5% of the counted population). Thus, the PES adjustment increases the 2010 census population to 245.9 million. The 8.3 million is distributed proportionally by age group and sex to the original population and the result is used as the base for population projections.

Table 7.3 Indonesian population in 2010, before and after PES adjustment

Age groups	2010 Census Male	2010 Census Female	2010 Census Male + Female	2010 Census adjusted by PES Male	2010 Census adjusted by PES Female	2010 Census adjusted by PES Male + Female
0	2,438,251	2,303,185	4,741,436	2,339,063	2,213,286	4,552,349
1–4	9,224,118	8,713,148	17,937,266	9,731,489	9,188,618	18,920,107
5–9	11,974,094	11,279,386	23,253,480	12,393,187	11,674,165	24,067,352
10–14	11,662,417	11,008,664	22,671,081	12,070,602	11,393,967	23,464,569
15–19	10,614,306	10,266,428	20,880,734	10,985,807	10,625,753	21,611,560
20–24	9,887,713	10,003,920	19,891,633	10,233,783	10,354,057	20,587,840
25–29	10,631,311	10,679,132	21,310,443	11,003,407	11,052,902	22,056,309
30–34	9,949,357	9,881,328	19,830,685	10,297,584	10,227,174	20,524,759
35–39	9,337,517	9,167,614	18,505,131	9,664,330	9,488,480	19,152,811
40–44	8,322,712	8,202,140	16,524,852	8,614,007	8,489,215	17,103,222
45–49	7,032,740	7,008,242	14,040,982	7,278,886	7,253,530	14,532,416
50–54	5,865,997	5,695,324	11,561,321	6,071,307	5,894,660	11,965,967
55–59	4,400,316	4,048,254	8,448,570	4,554,327	4,189,943	8,744,270
60–64	2,927,191	3,131,570	6,058,761	3,029,643	3,241,175	6,270,818
65–69	2,225,133	2,468,898	4,694,031	2,303,013	2,555,309	4,858,322
70–74	1,531,459	1,924,872	3,456,331	1,585,060	1,992,243	3,577,303
75–79	842,344	1,135,561	1,977,905	871,826	1,175,306	2,047,132
80–84	481,462	661,708	1,143,170	498,313	684,868	1,183,181
85–89	182,432	255,529	437,961	188,817	264,473	453,290
90–94	63,948	106,951	170,899	66,186	110,694	176,880
95+	36,095	68,559	104,654	37,358	70,959	108,317
Total	**119,630,913**	**118,010,413**	**237,641,326**	**123,817,995**	**122,140,777**	**245,958,772**

Using the PES adjustment to the population implies bigger projected population size in the future than previous projections have anticipated. For example, the projected population in 2010 by the ICBS (BPS et al., 2008) is about the same as the unadjusted 2010 census result. The medium fertility projections by the UN Population Prospects Revision 10 (hereafter called the UN projection) and the most plausible projection scenario by Muhidin (2002) resulted in a lower population size than did the 2010 PES adjusted census. Therefore, it is expected that the projections in this study will result in bigger future populations than has any previous projection.

B.2. Fertility Projection

Extrapolation is commonly used in fertility projections. McDonald (1979, 1981) for example used time series to project total births, outperforming the economic-demographic structural model in the short term. Keyfitz (1993) suggested that predicting the number of births is more parsimonious in many countries, as it is more constant than the birth rate. However, birth rate/fertility rate is also quite predictable, as the number of women is known as a certainty in the first 15 years (Booth, 2006), and projecting the fertility rate has had greater success (Congdon, 1980, 1989, McDonald, 1983). Over longer horizons, structural modelling may gain substantial accuracy (Ortega and Poncela, 2005).

Parameterisation of fertility has been developed for modelling. It sits between purely empirical and purely theoretical models (Booth, 2006). Parameterisation was developed for ASFR, such as the Coale and Trussel function (Coale and Trussell, 1974), which has been found to be superior (Hoem et al., 1981). Later, several modifications of this function were proposed (Knudsen et al., 1993, Rogers and Little, 1994). Another parameterisation in fertility that is commonly used is the Brass relational Gompertz model (Booth, 1984, Brass, 1981), which relates the observed fertility to a standard fertility. Lee (1993) developed a time-series model for ASFR, which also provides a new approach in incorporating uncertainty into the model (probability projections).

In this study, several options for the projection of fertility rate will be explored: 1) extrapolation of TFR with logistic function, 2) developing scenarios of future TFR from the opinion of experts and 3) the Brass relational Gompertz function of ASFR. The result of the projection will be compared to other methods in previous studies, particularly projections by the ICBS (BPS et al., 2008) and the UN Population Prospect 2010 (United Nations, 2011).

B.2.1. Total Fertility Rate

Most previous projections of TFR in Indonesia have used graphical extrapolations, either linear or exponential. Unchanged ASFR distribution by age is then assumed over time. The UN projection adopted double-logistic regression, which accommodates historical trends and variability of fertility in all countries, with the floor level of TFR 2.1.

The logistic function for TFR projection is formulated as follows:

$$TFR_t = 1.6 + \frac{k}{1+b\, e^{at}} \tag{7.1}$$

where : TFR_t = TFR estimate at time t

1.6	= lower asymptote, exogenous parameters
k	= constant ($k = U—1.6$)
U	= upper asymptote ($U = 6.2$)
a	= coefficient of logistic curve (also called growth rate)
b	= coefficient of logistic function
t	= dummy for year of estimation/projection; 1=1968, 2=1969, *etc*
e	= 2.71828

The lower asymptote of 1.6 is determined as the lowest possible (floor) value of TFR.[35] The upper asymptote (U) is calculated by adding 1.6 to the average of estimated TFR in Indonesia 1968–2006, which are the years of imputed fertility.

Over time, the TFR has declined. However, increased TFR in the most recent population census was recorded, triggering heated discussion and debates on how to interpret this increase. In terms of projection, it creates a challenge when the logistic function is to be used. Logistic function predicted the TFR at this period as 1.9, which is much lower than the 2010 census estimate (TFR 2.4). If this logistic regression were used, we would expect that in the next five-year period of projection, the TFR would be 1.9. This means a TFR decrease of 34% in just 5 years from 2010. Judging from the slower reduction in TFR in recent years, this sudden drop of TFR is unlikely. However, in the longer term, trends of TFR are more likely to follow the logistic function and converge at 1.6.

Alternatively, three different trend scenarios for TFR can be developed for the next 15 years; that is, high, medium and low fertility. The high fertility scenario assumes stable TFR from 2010 until 2025 at 2.4. It is unlikely that the increased TFR will continue in subsequent decades and exceed 2.4 (especially referring to the continuous decline of TFR in the past). The medium fertility scenario assumes a moderate decrease in TFR from 2.4 in 2010 to 2.1 in 2025. It seeks the path that is formatively needed to achieve the 2010–2025 Long-Term National Development Plan; that is, NRR=1 or TFR=2.1 by 2025. The low fertility scenario assumes a fast decrease of TFR from 2.4 in 2010 to

[35] In the UN Population Prospects Rev 10, TFR 1.6 is also set as the lower bound of 95% confidence interval of projected TFR in countries currently below replacement level.

1.69 in 2025. It seeks the trend experienced in low fertility countries in which TFR tends to converge at 1.6–1.85. The development of these scenarios has been the result of discussion and personal communication with experts.[36] Thus, these are subjective projections by expectation.

The Brass relational Gompertz function is also employed to project the future ASFR and TFR using information of ASFR from past censuses. The Brass model proposed that the proportion of total fertility experienced up to age x is assumed to follow the Gompertz distribution function:

$$\frac{F(x)}{TFR} = e^{Ae^{Bx}} \tag{7.2}$$

Where $F(x)$ = age-specific fertility cumulated to age x
TFR = Total fertility rate
A and B are constant with A<0.

Following transformation, A and B can be estimated with a linear function:

$$\eta\, F_x = \alpha + \beta \eta\, F_s(x) \tag{7.3}$$

where $F_s(x)$ is a standard pattern and is provided. This standard was derived by Booth (1984). α and β are solved using least linear regression on available points. In the model, α is taken as the age by which half of the total childbearing has occurred, and β may be interpreted as the spread or degree of concentration of the schedule (United Nations, 1983).

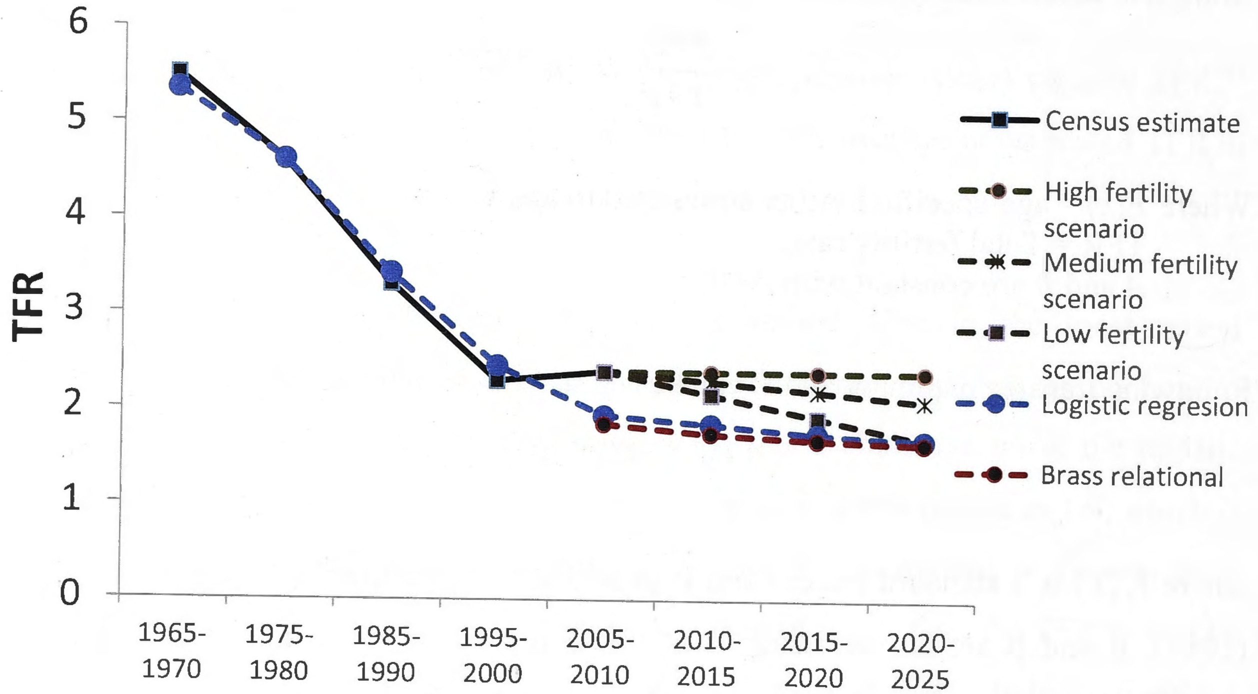
Table 7.4 Projection of TFR 2005–2025 by methods of projection

Projection methods	Projected TFR			
	2005–2010	2010–2015	2015–2020	2020–2025
Logistic regression	1.94	1.85	1.75	1.69
Brass relational model	1.85	1.75	1.69	1.65
High fertility scenario	2.40	2.40	2.40	2.40
Medium fertility scenario	2.40	2.30	2.20	2.10
Low fertility scenario	2.40	2.16	1.93	1.69

[36] Personal communication and discussion with Prof. Peter F. McDonald and Prof. Terence H. Hull of the Australian Demographic and Social Research Institute, the Australian National University.

The results show that mathematical modelling produced lower fertility (1.65 for the Brass relational model and 1.69 for the logistic function model) in 2025 than the expectation model (except of in the low fertility scenario) for the period 2020–2025. The projected TFR in the mathematical model is low because the model gives the same weight for each imputed TFR prior to 2005. Consequently, the sudden increase of TFR in the 2010 census had less of an effect in the projections.

Figure 7.9 Trend of estimated and projected TFR in Indonesia by projection method



The result of the mathematical model is closer to the UN projection of a medium fertility scenario, which projected a TFR of 1.85 for the 2020–2025 period. The high and low fertility scenarios of the UN projected TFRs of 2.35 and 1.35 in 2020–2025, respectively. Thus, all projection methods used (except for the high-fertility scenario) projected that TFR falls between the high and low-fertility scenarios of the UN projection.

B.2.2. Age-Specific Fertility Rate

ASFR is a decomposed version of TFR by age of the mother, usually according to five-year groupings. In decomposing TFR into ASFR for the projected population of 2010–2025, two different calculations are assumed: constant ASFR proportion and change in proportion due to timing changes.

For constant proportion of ASFR, it is assumed that proportion of fertility for each age group to TFR remains the same with the proportion of TFR in 2010. In this way, it is assumed that any change in total fertility affects all age groups to the same degree. Referring to past ASFR estimates by several censuses (see Figure 7.5), this may not be the case. Instead, there appears to be a shift in fertility from younger to older women. However, the change is small and the effects to the projection may not be significant. In fact, most projections of Indonesian population assume a constant proportion of fertility.

In the Brass relational method, the proportion of fertility by age group is determined by two parameters (α and β), which are derived using a mathematical function from past ASFR data. Table 7.5 presents the estimated and linearly projected α and β using ASFR data from the 1970, 1980, 1990, 2000 and 2010 censuses.

Table 7.5 Parameter of estimates, Brass relational model and their projection 2010–2025

Reference year	α	β	Data source/Methods
	Estimated		
1968	-0.4649	1.1022	1970 census
1977	-0.4475	1.1300	1980 census
1987	-0.4209	1.1531	1990 census
1997	-0.3015	1.0264	2000 census
2007	-0.3257	1.1892	2020 census
	Projected		
2010	-0.2936	1.1364	Linear regression
2015	-0.2719	1.1400	Linear regression
2020	-0.2502	1.1436	Linear regression
2025	-0.2285	1.1472	Linear regression
2030	-0.2068	1.1507	Linear regression

Data source: Calculated using ASFR in various years of censuses.

Using the projected α and β parameters to calculate ASFR and TFR 2010–2025, the projected TFR is very close to the TFR projected using the logistic function (see Figure 10). However, it is different from other ASFR projections that assume a constant proportion of fertility. The Brass relational model projected the proportion of fertility to decline in younger groups and increase in older groups, continuing the change in timing found in previous census estimates.

Figure 7.10 Age-specific fertility rates, projected using mathematical model

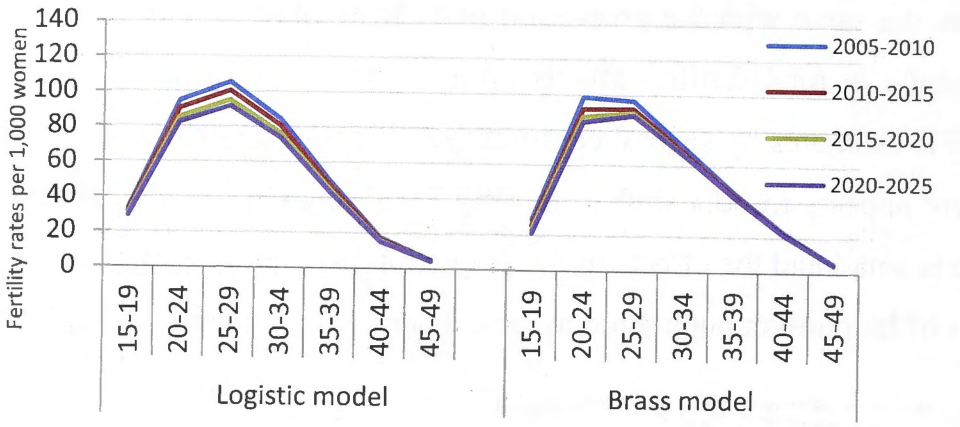
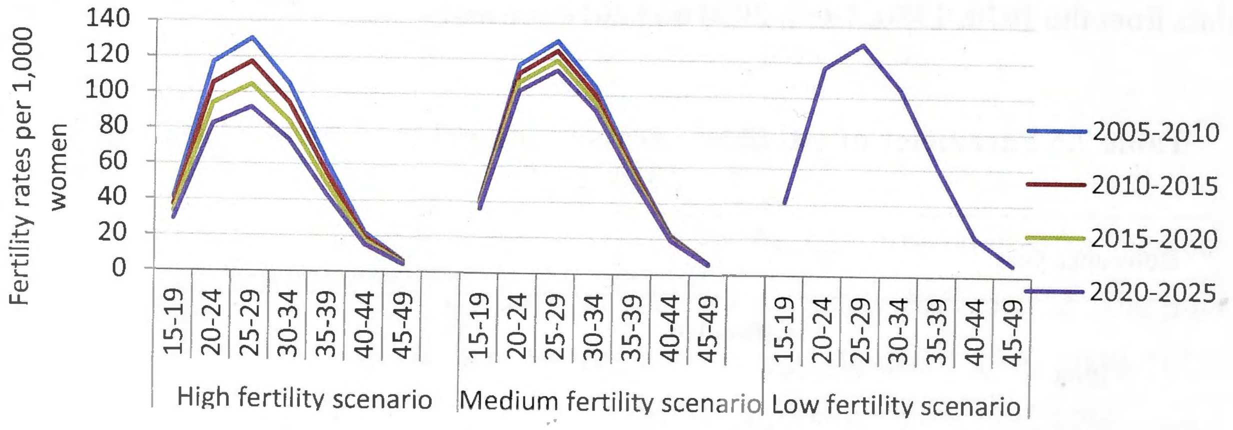


Figure 7.11 Age-specific fertility rates, projected using expectation



Among all alternatives of the projected TFR and ASFR 2010–2025, the mathematical models produce lower TFRs in earlier projection periods. For the 2010 data point, logistic function projected a TFR of 1.94 and the Brass relational model projected 1.85, both of which are much lower than the 2010 census TFR estimate of 2.4. At the end of the projection period (2020–2025), however, the projected TFRs seem plausible if the extrapolations for TFR decline in the past five decades are considered.

Judging the possibility of various paths of fertility decline, this study accommodates various expectations. The Brass model provides an advantage by taking change in timing into account in the model. However, the effect is probably small. Further, the Brass model, like the logistic model, produces an implausibly sharp fertility decline between 2010 and 2015. Even though plausible in the long run, the logistic model is likely to overshoot fertility decline between 2010 and 2015. Therefore, the projections of all three scenarios of fertility decline by expectation (high, medium and low fertility scenarios) will be used to project the future population. These projections are given in Appendices 10–12.

B.3. Mortality Projection

There are various methods of mortality projection/forecasting, including simple extrapolation, parameterisation of one or more functions of mortality, relational model of mortality, Lee-Carter mortality forecasting method, generalised linear model, forecast based on cohorts model, forecasting by cause of death and structural approaches (Booth, 2006). The choice of method is more limited in developing countries, including in Indonesia, due to restricted time series data and other data limitations. The following discussion will briefly examine the mortality projection methods that are sensible and commonly used for population projection in Indonesia.

Civil registration of death is not available in Indonesia and mortality is usually estimated from a census or survey. However, most surveys fail to capture adult mortality. Only recently in the 2010 census was adult mortality recorded in more detail, including information on the sex and age of the deceased. Data on infant mortality can be used to estimate adult mortality and hence create mortality schedules using a model life table. Usually, the West model is used to generate mortality schedules (BPS et al., 2008, Muhidin, 2002), with only a few projections having used the UN General Model (Nitisastro, 2006). A Helligman-Pollard parameterisation of Susenas data was used in the projection by Muhidin (2002). Although relational models of mortality (Brass, 1971) may also be employed, there has been no attempt to do so in Indonesia.

In this study, IMR is used as the parameter in projecting the trend of mortality rate in the future. The projected IMR then will be used as the criteria to choose the level of life expectancy in the West model life table, from which the schedule of mortality or age–specific death rate (ASDR) will be derived. The use of a model life table implies that even though there is a reduction in overall mortality, the pattern of mortality is assumed constant over the projection period.

The logistic model will be used in the projection of future mortality.

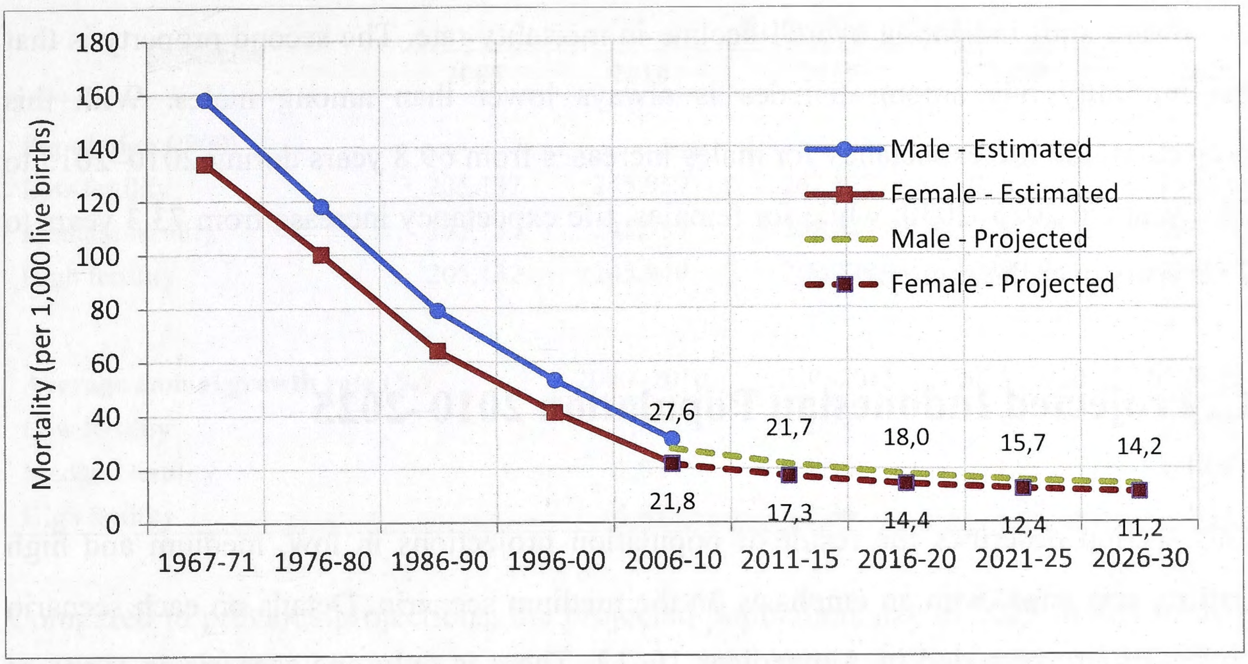
$$IMR_t = m + \frac{k}{1+b\ e^{at}} \qquad (7.4)$$

where: IMR_t = IMR estimate at time t
m = lower asymptote of IMR, exogenous parameters (12 for males; 9 for females)
k = constant (k=U–m)
U = upper asymptote of IMR (172 males; 169 females)
a = coefficient of logistic curve (also called growth rate)
b = coefficient of logistic function
t = dummy for year of estimation/projection; 1=1968, 2=1969, *etc*
e = 2.71828

Lower asymptotes for males and females were derived from the lowest IMR at provincial level recorded in the 2010 census. Both are IMRs recorded for DKI Jakarta province. Thus, the model assumes that nationally IMR will eventually decrease to 12 deaths per 1,000 live births for males and 9 deaths per 1,000 live births for females.

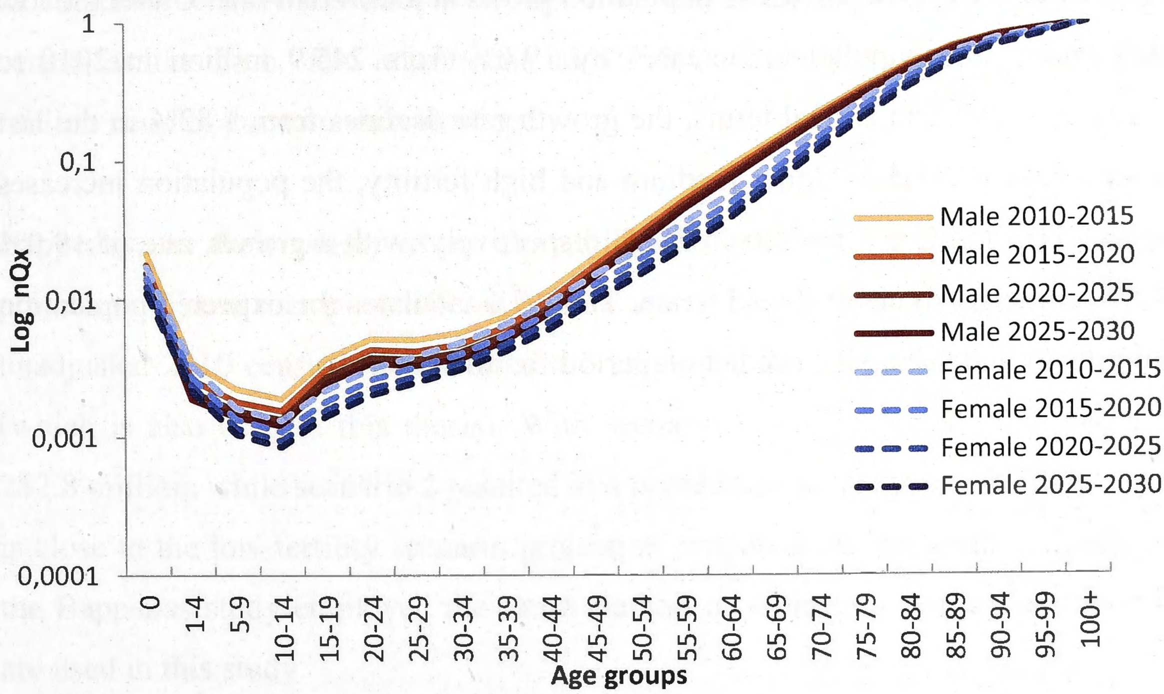
Figure 7.12 shows the IMR estimates from previous censuses (1970, 1980, 1990, 2000 and 2010), which are calculated using the Brass own-child method. This figure also shows the projected IMR for 2010–2030, calculated using logistic regression based on the estimated IMR from the previous censuses. In this model, the trend of IMR reaches hard rock; that is, *the* point after which the decline in IMR slows. By 2026–2030, IMR among males reaches 14.2 deaths per 1,000 live births, while among females, it reaches 11.2 deaths per 1,000 live births.

Figure 7.12 Estimates and projections of IMR in Indonesia by sex



The projected IMR is used to choose the appropriate level of life expectancy in the West model life table, to obtain the ASDR, which in turn is used together with other parameters to calculate the growth of the population. The projected mortality schedule for males and females is presented graphically in Figure 7.13.

Figure 7.13 Projected mortality schedule for males and females 2010–2030



From the period 2010–2015 to 2025–2030, the pattern of mortality is the same, with the downward shift indicating overall decline in mortality rate. The second property is that the mortality rate among females is always lower than among males. With this projection, the life expectancy for males increases from 69.8 years during 2010–2015 to 74.1 years in 2025–2030; while for females, life expectancy increase from 73.3 years to 78.9 years over the same period.

C. Projected Indonesian Population 2010–2025

This section describes the result of population projections in low, medium and high fertility scenarios, with an emphasis on the medium scenario. Details on each scenario projection are provided in Appendices 10–12. There is only one scenario in terms of mortality trend and mortality schedule; while net international migration is assumed to be zero. Consequently, any differences in the projected population stem from the different levels of the fertility assumptions.

C.1. Population Size

In each level of fertility assumed, the population grows at a different rate. Under the low fertility scenario, the population increases by 19.6% from 245.9 million in 2010 to 291.1 million in 2025. In annual terms, the growth rate declines from 1.82% in the last decade to 0.90% in 2025.[37] Under medium and high fertility, the population increases slightly to 294.1 and 296.4 million in 2025, respectively, with a growth rate of 19.9% and 20.8%, respectively, over the 15 years. Table 7.6 tabulates the expected population size and growth rate during the prediction period for all scenarios.

[37] Annual growth is the average exponential rate of growth of the population over a given period. It is calculated as $ln(Pt/P0)/t$, where $P0$ is the initial population in 2010, Pt is the population in time t and t is the length of the period. It is expressed as a percentage.

Table 7.6 Projected population size and growth rates 2005–2025 (in thousands)

Scenarios	Projection period				
	2005	2010	2015	2020	2025
Population ('000)					
Low fertility	205,132	245,959	262,537	278,210	291,056
Medium fertility	205,132	245,959	262,677	279,183	294,113
High fertility	205,132	245,949	262,779	279,896	296,353
Average annual growth rate (%)		2000–2010	2010–2015	2015–2020	2020–2025
Low fertility		1.82	1.34	1.17	0.90
Medium fertility		1.82	1.35	1.23	1.04
High fertility		1.81	1.36	1.27	1.14

Compared to previous projections, the projected population size in 2025 in this study is substantively larger, even when the low fertility scenario is used in the comparison. The ICBS's projected population size for 2025 (BPS et al., 2008) is 273.2 million, assuming that IMR and TFR decline according to the logistic function and the pattern of mortality and fertility remains constant. The plausible scenarios (fertility and mortality change in pattern and level) in Muhidin (2002) projected that the population of Indonesia in 2020 would be 261.4 million, and the UN projection (medium fertility scenario) gave the population at 271.9 million by 2025. The larger population size in this projection, even in the lower fertility scenario, is owing to the use of the PES adjusted 2010 population census as the base. The adjustment adds 3.5% to the 2010 census population (8.3 million people) due to undercounting.

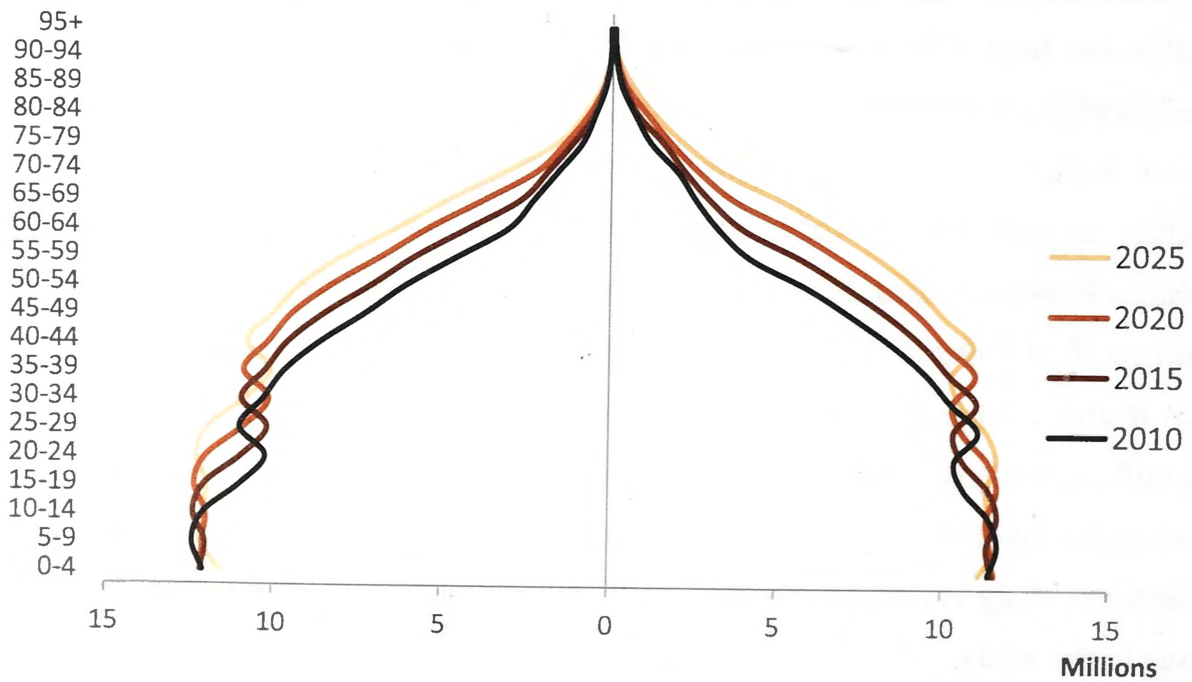
Bappenas, in their policy study (unpublished), built two scenarios for population projection. These scenarios differed in their use of base population. Scenario 1 used the unadjusted 2010 census, while scenario 2 employed the PES adjusted 2010 population (which is also used in this thesis). With scenario 1, the projected 2025 population is 282.8 million, while scenario 2 resulted in a population size of 292.7 million. This result is close to the low fertility scenario projection proposed for this study. All scenarios in the Bappenas study employed the same method in projecting fertility and mortality as are used in this study.

C.2. Population Structure

Between 2010 and 2025, the number of adults (age 15+) in the population is expected to increase significantly. The age of the population is also expected to increase, although, in terms of the proportion to total population, this increase will be relatively small. The proportion of children, on the other hand, is projected to decrease. Previously, ICBS projected that 2016 was the year in which the total number of births would start to continuously decline until the end of the projection period in 2025 (BPS et al., 2008). Another projection by the UN also shows a decline in the total number of births in Indonesia until 2010.

Even though infant mortality continues to decline, the speed of this decline is surpassed by the decline in fertility, resulting in a decline in the number of births and subsequently in the number of children. In the absence of migration, the only driver for change in adult population size in the three scenarios of fertility in the projections of this study is cohort size and mortality. The decreasing adult mortality rate can thus be expected to result in an increased proportion of adults and elderly in the population.

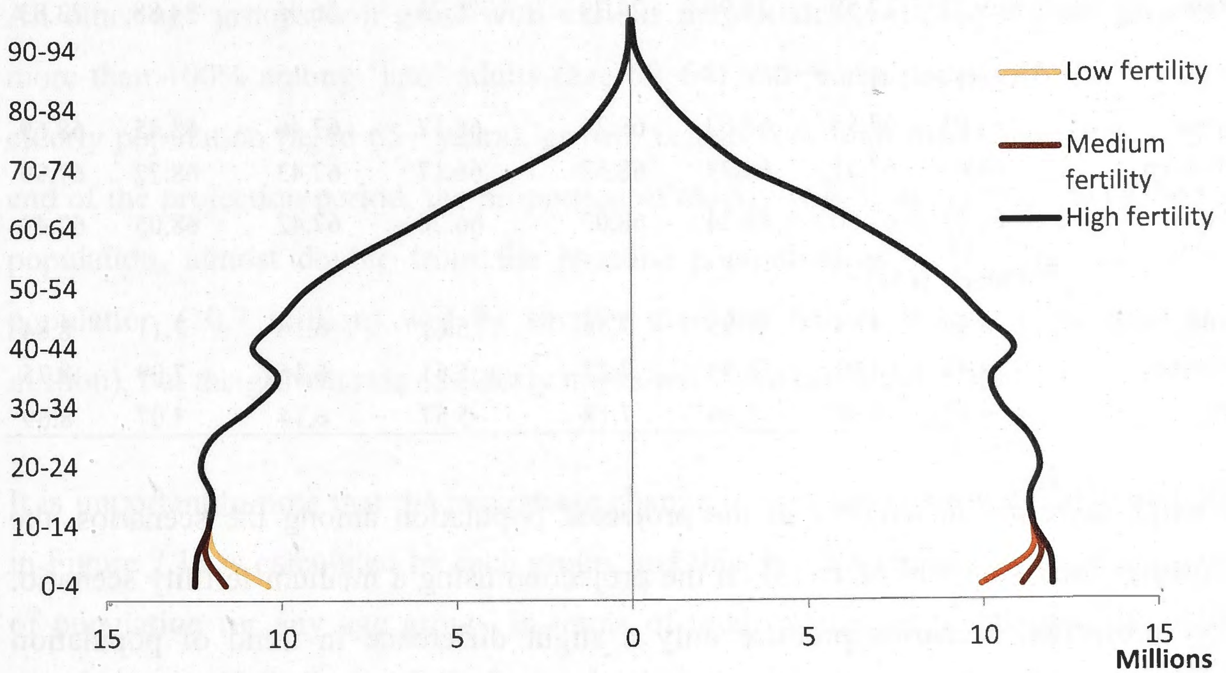
Figure 7.14 Population pyramid 2010–2025



The structure of the population by age is not significantly different among the three fertility scenarios. Since the only difference between the scenarios is in the fertility rate, the only affected population structure is at the bottom of the pyramid, reflecting the difference in the number of births for each projection period and the proportion of the population aged 0–4 and 5–9 years in the subsequent projection periods. No effect will be seen on the other age groups, unless longer periods of projection were to be performed. Thus, in terms of structure, the effect of fertility in the short term is isolated to the younger population group.

Figure 7.15 shows the population pyramid in the projection period for each scenario. These scenarios do not exhibit any significant differences. In fact, if the projected population from the same period but different scenarios are overlaid on each other, the only noticeable difference is in the bottom of the pyramid, showing that lower fertility rate will decrease the number of births in the population.

Figure 7.15 Overlays of projected Indonesian population pyramid 2025, by fertility scenario



In terms of the proportion of children (aged 0–14), all scenarios project a smaller proportion of children and higher proportion of adults and the elderly in 2025 as compared to in 2010. The source of variation in the proportion of population groups is the change in the number of children, affected by the different fertility scenarios.

However, since the projection period is quite short (three periods, each with a five-year span), the effect of fertility can be observed among only the age groups 0–4, 5–9 and 10–15. For age group 15+, all projections in the same projection years resulted in the same number of population.

Table 7.7 shows the population structure by comparing the change in the proportion of children, adults and the elderly to total population in each projection period. In all scenarios, the proportion of children decreases, while the proportion of adults and the elderly increases.

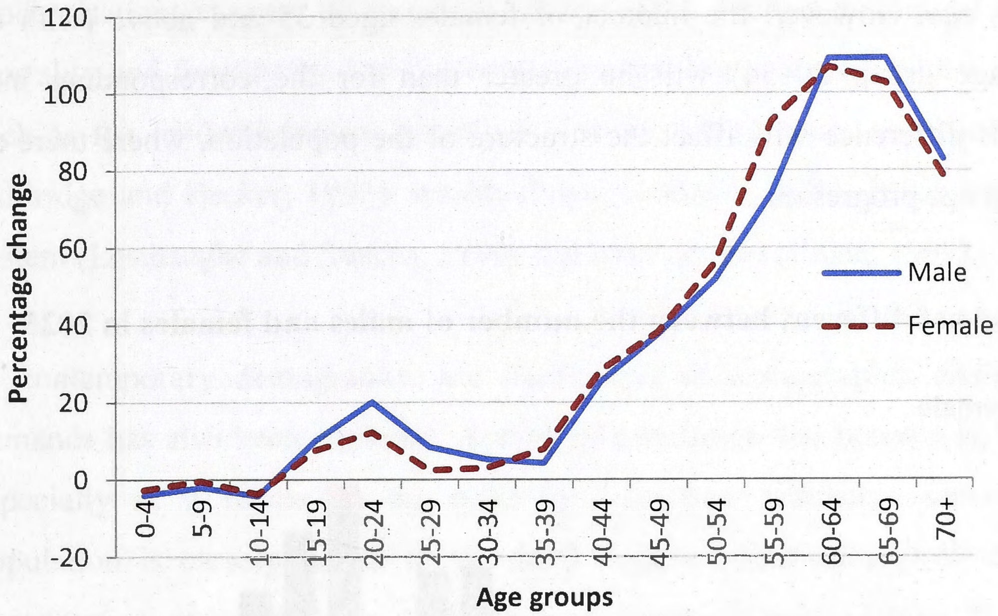
Table 7.7 Change in proportion of population groups to total population (%) 2010–2025, by fertility scenarios

Fertility scenario	Proportion to total population (%)							
	Male				Female			
	2010	2015	2020	2025	2010	2015	2020	2025
	Children (0–14)							
Low	29.51	27.51	25.42	23.40	28.22	26.38	24.43	22.47
Medium	29.51	27.55	25.69	24.20	28.22	26.41	24.69	23.26
High	29.52	27.59	25.90	24.79	28.23	26.45	24.88	23.83
	Adult (0–14)							
Low	66.01	67.55	68.62	69.26	66.17	67.46	68.45	68.69
Medium	66.01	67.51	68.38	68.52	66.17	67.43	68.22	67.99
High	66.05	67.50	68.24	68.02	66.20	67.42	68.05	67.49
	Elderly (65+)							
Low	4.48	4.94	5.95	7.35	5.61	6.16	7.11	8.84
Medium	4.48	4.93	5.93	7.27	5.61	6.16	7.09	8.75
High	4.43	4.91	5.86	7.18	5.57	6.14	7.07	8.69

Although there are differences in the projected population among the scenarios, the following discussion will be based on the projection using a medium fertility scenario. Other projection scenarios produce only a slight difference in trend of population structure, and therefore medium fertility is sufficient as a case to describe the general change in population structure for 2010–2025.

The successive decrease of fertility results in the negative growth in the number of children. Children at age groups 0–4, 5–9 and 10–14 years will decrease by 4.0, 2.0 and 0.1 for males and 2.6, 0.3 and +0.2 (increased) for females, respectively, between 2010 and 2025. In addition, although there are increases in the number of women of childbearing age, the total number of births will still decrease by 13% over the next 15 years.

Figure 7.16 Changes in population (%) 2010–2025, by age groups and sex

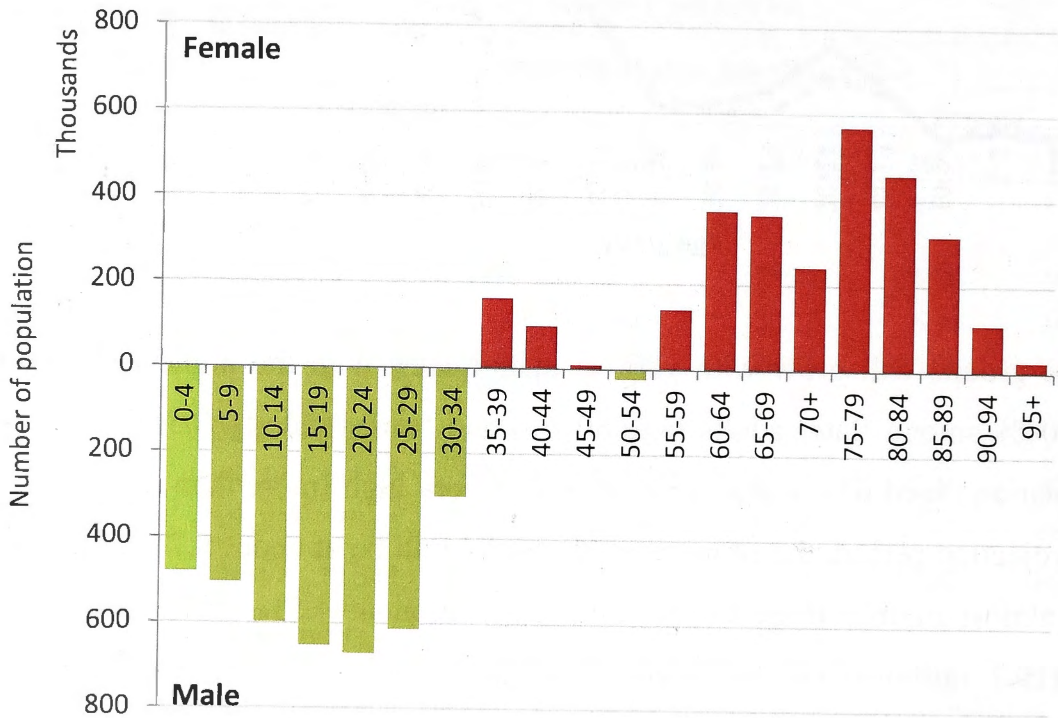


All other age groups will grow with various magnitudes, with the highest growth of more than 100% among 'late' adults (age 60–64) and 'early' elderly (65–69). For the elderly population (aged 65+ years), growth is also very high (more than 80%). At the end of the projection period, the proportion of elderly will be at about 8.7% of the total population, almost double from the baseline population at 4.5%. The male elderly population (10.7 million) will be smaller than the female elderly population (12.9 million), but the growth rate of elderly males will have exceeded that of females.

It is important to note that the percentage change in population between 2010 and 2025 in Figure 7.16 is calculated by each group, and thus is not weighted to the total number of population for any age group. In terms of total number of population, the elderly population is relatively small. Referring back to the population pyramid in Figure 7.16, the biggest increase in the number of population is among adults, both for men and women. However, the change for each group is very important, especially for particular groups of interest. For example, the government's child health division may express interest in the 13% decrease in the total number of children, while the social security office will likely consider the increase in the proportion of elderly people as a major challenge for maintaining this cohort into their old age.

Figure 7.17 shows the likely net difference between males and females for each age group for 2025. By 2025, the number of males aged 0–34 will be higher than for females of this age. However, the number of females aged 35 and above (with the exception of age group 50–54) will be greater than for the corresponding male population. This difference will affect the structure of the population, where there are more females as age progresses.

Figure 7.17 The net different between the number of males and females in 2025



D. Population and Society Changes

Population growth is not an isolated process. The linkage of births, deaths and migration to epidemiological, social, economic, political and environmental dimensions means that population growth both follows and is followed by other factors. This section will briefly assess the possible changes in the characteristics of the future Indonesian population that are closely related to demand for healthcare.

The association of demographic changes and social economic development and culture has been proposed since the emergence of demographic transition theory. The three demographic regimes (primitive, intermediate and contemporary) suggested by Adolphe Landry (Landry, 1987) link the historical development of mortality and fertility with the overall stage of a country. Demographic transition gives a description of the modernisation progress of a society (Kirk, 1996). Further theoretical development of mortality and fertility tried to associate demographic processes with a variety of fields such as the epidemiological transition (Omran, 1971), costs and benefits of children (Aldridge and Becker, 1993), wealth flows (Caldwell, 1980, 2005), shift in ideational system (Lesthaeghe and Surkyn, 1988) and birth control (Coale, 1969).

In contemporary demography, the association of demographic changes and health demands has also been explored. Ageing of population has become an emerging issue, especially as it relates to the need for improved healthcare services. An ageing population is closely linked to the third stage of epidemiological transition, where degenerative, stress and man-made diseases emerge (Omran, 1998). Thus, the size and structure of population interactions, along with the state of epidemiology and social economic conditions, are very important when planning health systems.

In the case of Indonesia, as the population size grows and the structure changes, it is expected that the effects on demand for healthcare will be significant. The effect would not only be driven by demographic change, but also by social economy developments (for example, the provision of insurance) and transitions in epidemiology (such as in the emergence of non-communicable diseases as the main cause of death). In Chapters 4, 5 and 6, the associations between various demographic, social economy and health need factors and demand for healthcare are elaborated upon. In the next chapter, these associations will be extended to the future projected population.

Chapter 8
Healthcare Utilisation of the Future Population

Previous chapters have shown that demographic characteristics have significant effects on healthcare utilisation in Indonesia. Demographic changes, such as increase in size and structure of the population, will likely affect healthcare utilisation in the future. In addition, demographic change, led by declining fertility and mortality, is often accompanied by improved social economic status (SES), epidemiological transition and public interventions, such as social health insurance. These non-demographic factors are also influential in healthcare utilisation. The extent of the influence of demographic and non-demographic factors on future healthcare utilisation, however, is largely unknown.

This chapter is primarily intended to assess and compare the effects of demographic and non-demographic factors on healthcare utilisation in the future. Accommodating non-demographic factors in the projection can be very complicated and painstaking. The degree of difficulty and uncertainty grows with the number of variables, so that it is necessary to limit the number of variables in the projection. This study selects two non-demographic characteristics (health insurance subscription rate and communicable disease rate in the population) as an example of how they influence future healthcare utilisation.

This chapter begins with a brief overview of the potential effects of demographic and non-demographic factors on healthcare utilisation in the future, followed by a discussion on approaches for the projection of healthcare utilisation. Finally, the projection result will be analysed and discussed. A brief discussion on the projection results will also be presented.

A. Introduction

Demographic change in Indonesia potentially affects healthcare utilisation through the increased size of the population and the changes in the structure of the population in terms of age and sex. By assuming that propensity of utilisation remains the same for each sex and age group of population, the overall utilisation in the future is expected to increase with the number of the population.

The determinants analysis in Chapter 4 suggested various non-demographic factors such as income, education, health insurance rate and pattern of morbidity as influential in the decision to utilise healthcare, and these factors will likely affect the size and pattern of utilisation in the future. Thus far, however, no attempt has been conducted to accommodate non-demographic factors into health utilisation projections. In this study, in addition to demographic change, the effects of health insurance and chronic disease will be investigated to provide an example of how demographic and non-demographic factors interact, and how these interactions are likely to affect future healthcare utilisation.

Health insurance is chosen as a factor because of its association with healthcare utilisation (see Chapter 4) and choice of provider (see Chapter 5). This association is also supported by previous studies in Indonesia (Hidayat et al., 2004, Hidayat, 2008, Pradhan et al., 2007, Rokx et al., 2010, Sparrow et al., 2010) and in other countries (Buchmueller et al., 2005, Cassedy et al., 2008, Lu and Hsiao, 2003, Manning et al., 1987, Newacheck et al., 1998). From a public policy perspective, the introduction of health insurance for the poor and the government's plans to achieve universal health coverage in the coming years provide a good case for evaluating the role of policy measures in affecting overall healthcare utilisation.

Chronic disease in Indonesia has been on the rise as the main cause of deaths in the last decades, parallel with the decline in communicable disease. This trend is referred to as epidemiological transition (Omran, 1971), although the precise stage of the transition is not clear, with re-emergence of infectious disease (Barrett et al., 1998, Omran, 2005). Being diagnosed with chronic diseases has been identified as one of the strongest variables explaining variations in healthcare utilisation (see Chapter 4). With prevalence of chronic ill health varying widely between age groups, it is interesting to know whether chronic illness will influence the size and pattern of utilisation in the future.

B. Model Development and Data Sources

Various methods have been used for forecasting or projecting future demand for healthcare, including mathematical extrapolation (Abdel-Aal and Mangoud, 1998, Burner et al., 1992, Lovell et al., 2009, Kao and Tung, 1980, O'Brien-Pallas et al., 2001, Scheffler et al., 2008, Xue et al., 2001), need-based projections (Birch et al., 1994, Gibbs et al., 2008, Lee and Miller, 2002), structural modelling (Watanabe and Tsubo, 1995) and actuarial and propensity methods (Hall et al., 1975, Johnston and Teasdale, 1999, Mouza, 2002, Reinhardt, 2003, Schofield and Earnest, 2006, Strunk et al., 2006, Warren et al., 2008). An overview on the available methods for demand for healthcare projections was provided in Chapter 2.

Mathematical extrapolation may predict healthcare utilisation well in the short term. However, the abrupt change in the utilisation rate in Indonesia in the last decade makes it difficult to use past data as the basis for extrapolation. Structural relationships may not be the best choice for projection, considering the limitations in understanding the relevant variables.

The propensity model is a promising option, without too much complexity. For this reason, it has been chosen as the method of projection for this study. The propensity model is the most common method of projection of future utilisation and has been used in Australia (Schofield and Earnest, 2006), Hawaii, the US (Hawaii Health Information Corporation, 2004), Canada (Stewart et al., 2002) and Greece (Mouza, 2002), as well as elsewhere in the world. This method can also be performed stochastically; for example, by introducing variation in the predictive variables.

Assuming that the propensity to seek medical care for an individual of a certain age and sex is constant over time, the variation in the rate of increase in utilisation in the projected population should correlate to changes in the size and structure of the population. In this way, the projection will isolate the effect of sex and age on healthcare utilisation, attributing this to demographic effects only.

When health insurance and chronic diseases are introduced to the model, the propensity of seeking medical care for a person with or without health insurance or chronic diseases is assumed constant over time for a given sex and age group. As a result, the difference, if any, in total utilisation in the future is attributable to changes in demographic characteristics, health insurance rates or chronic disease rates. The net effect of health insurance or chronic diseases is calculated by subtracting the projected total utilisation to the projected utilisation due to demographic change.

Throughout the chapter, the effect of demographics, health insurance subscription rate and chronic disease rate will be evaluated in terms of the magnitude and the pattern. Magnitude of utilisation reflects the change in the rate of utilisation, both total and by population groups. Pattern of utilisation indicates the change in contribution of a group of population (by sex, age, health insurance or chronic illness) to total utilisation.

The models are formulated as follows:

$$U_t = \sum_i^2 \sum_{k=0-4}^n \rho_{ik} N_{ikt} S_{ikt} \tag{8.1}$$

$$U_t = \sum_i^2 \sum_{k=0-4}^n \rho_{ik} N_{ikt} \tag{8.2}$$

$$\mathrm{U_{tr}} = \sum_\mathrm{i}^2 \sum_{\mathrm{k}=0-4}^\mathrm{n} \sum_\mathrm{r}^2 \rho_\mathrm{ikr} \mathrm{N_{ikr}} \mathrm{S_{ikrt}} \tag{8.3}$$

$$U_{tc} = \sum_i^2 \sum_{k=0-4}^n \sum_c^2 \rho_{ikc} N_{ikc} \tag{8.4}$$

where U = number of utilisation of healthcare

N = number of population

S = sickness rate (percentage of population who are ill)

ρ = mean probability of seeking medical care when ill (Estimated from 2007 Susenas for Equation 8.1 and 8.3 and from 2007 IFLS for Equation 8.2 and 8.4)

i = sex (1=males; 2=females)

k = 5-year age grouping (0–4, 5–9,. . . . ,n)

t = year of projection (2010, 2015, 2020, 2025)

r = insurance subscription status (1=insured; 2=not insured)

c = chronic disease status (1=chronic disease is diagnosed; 2=no chronic disease diagnosed)

Parameter ρ (probability to seek medical care when ill) is an intrinsic value and is time invariant; assuming the likelihood of seeking medical care when sick is constant over the projection periods for a given age, sex and insurance or chronic disease status. U_t is the projected utilisation due to demographic change (the demographic effect), $U_{tr}-U_t$ is the insurance subscription effect and $U_{tc}-U_t$ is the chronic disease effect. The utilisation of healthcare is calculated for each age group and sex, and therefore it does not assume a monotonic (linear) effect for age on healthcare utilisation.

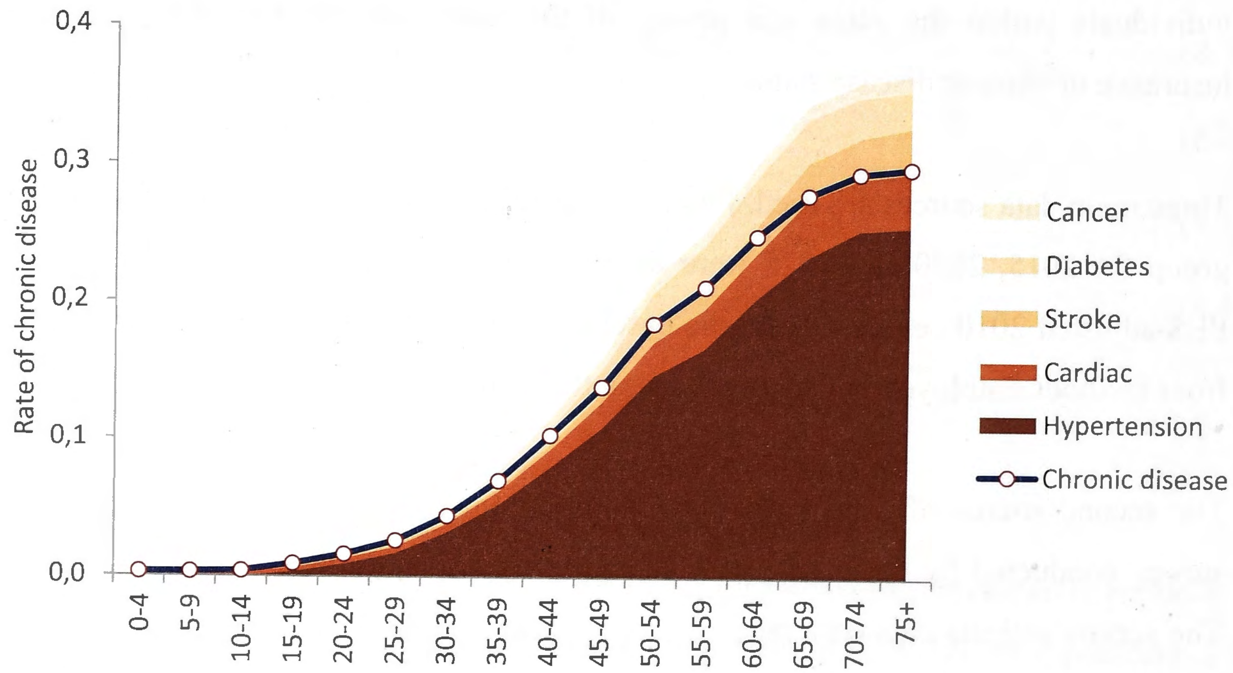
The probability to visit (ρ) for each sex and age group, and further, for people with and without insurance, was estimated using logistic regression. The independent variables were age group (by five-year range), sex and health insurance subscription status. Propensity for people with or without chronic disease was estimated using logistic regression and data from the 2007 Riskesdas, with independent variables including age group (by five-year range), sex and chronic disease status. Since there were no covariates included in the model, there was no variation in the predicted ρ among individuals within the same age group, of the same sex, or with the same health insurance or chronic disease status.

Three main data sources are used. First, data on the projected population by sex and age group for 2015, 2020 and 2025 were drawn from cohort component projections with PES-adjusted 2010 census data as the baseline. This projected population was obtained from methods employed in Chapter 7, using the medium fertility scenario.

The second source of data is the 2007 Susenas. Susenas is an annual cross-sectional survey conducted by the ICBS, with a sample size of more than 250,000 households. The survey collects data on a range of social, economic and housing indices, as well as other information from stratified randomised household samples. The health module seeks information of sickness symptoms, outpatient and inpatient visits in the last one month and health insurance subscription status. However, information on outpatient and inpatient visits is only available for those who reported themselves as having sickness symptoms. Since the pattern and probability of seeking healthcare for those who did not indicate themselves of having sickness symptoms is unknown, the effects of health insurance can only be calculated for the ill population (see Equations 8.1 and 8.3).

The third data source is the 2007 Basic Health Survey (Riskesdas), which was conducted nationally by the Ministry of Health in 2007. Riskesdas collects, among others things, information on demographic characteristics, outpatient healthcare utilisation and whether a person has been diagnosed with a chronic disease by health professionals. This is the only national survey that collects information on chronic diseases. Since data on outpatient visits are collected regardless of the presence of sickness symptoms in the last four weeks prior to the interview, Equations 8.2 and 8.4 are used for the calculation. Thus, unlike the analysis on the effects of health insurance, which is only valid for ill people, the effects of chronic disease can be calculated for all samples. In this study, an individual is assigned with a chronic disease if he or she reported having been diagnosed by health professionals with one or more of the following disease: hypertension, cardiac disease, stroke, diabetes and cancer (see Figure 8.1). Thus, this variable also accommodated chronic co-morbidity.

Figure 8.1 Rate of non-communicable disease by type and age group



Notes: Chronic disease morbidity is defined as having been diagnosed with at least one chronic disease: diabetes, stroke, cardiac disease and hypertension. This variable is used in the model.

Figure 8.1 shows the proportion of the population that have been diagnosed with cancer, diabetes, stroke, cardiac disease and hypertension. The chronic disease labels in the graph represent people that have been diagnosed with at least one chronic disease. The proportion of people diagnosed with chronic diseases increases with age, and the most prevalent disease diagnosed is hypertension. (Details on the prevalence of chronic diseases are presented in Appendix 13 and 14).

C. Input Data for Projections

Table 8.1 summarises the sets of assumptions and data input for the healthcare utilisation projection.

Table 8.1 Assumption and estimation methods of input data for projection of healthcare utilisation

Variables	Projection/Assumption	Estimation methods
Population size & structure (N_t)	Increased by 13%, early ageing	Cohort component method (Chapter 7)
Probability of utilisation (p)	Constant (2007 probability)	Binomial logistic regression
Sickness rate (S_t)*	Constant (2007 rate)	-
Health insurance rate	Increased from 29% to 100% in 2015, *maintained afterward*	Linear Extrapolation
Chronic disease rate	Increased from 6.8% to 14.3% *(annual increase of 0.5 pp)*	Linear Extrapolation

Notes: *Sickness rate is needed for calculating the effect of health insurance using 2007 Susenas data

Population profiles by sex and age group are taken from estimated population 2010 and projected population 2015, 2020 and 2025, using the medium fertility scenarios. Although the different scenarios of fertility will result in different rates of increase in utilisation, in terms of pattern and relative comparison they will be similar. Therefore, instead of exploring the different population scenarios, this analysis will focus on comparing the effect of demographic and non-demographic factors in the most likely population profile in the future; that is, the medium fertility scenario.

Probability of utilisation (p) is a predicted probability value estimated using a binomial logistic regression with limited independent variables, to reduce standard errors. Two sets of p are estimated: one set from the 2007 Susenas, as the probability of utilisation for different health insurance subscription status groups; and the second from the 2007 Riskesdas data, for probability utilisation by chronic disease status. Both are calculated for both sexes and by age group. In the regression, p is the probability of a given age or sex cohort seeking medical care.

Table 8.2 Probability of utilisation (p) by sex and age group, according to health insurance subscription and chronic disease status

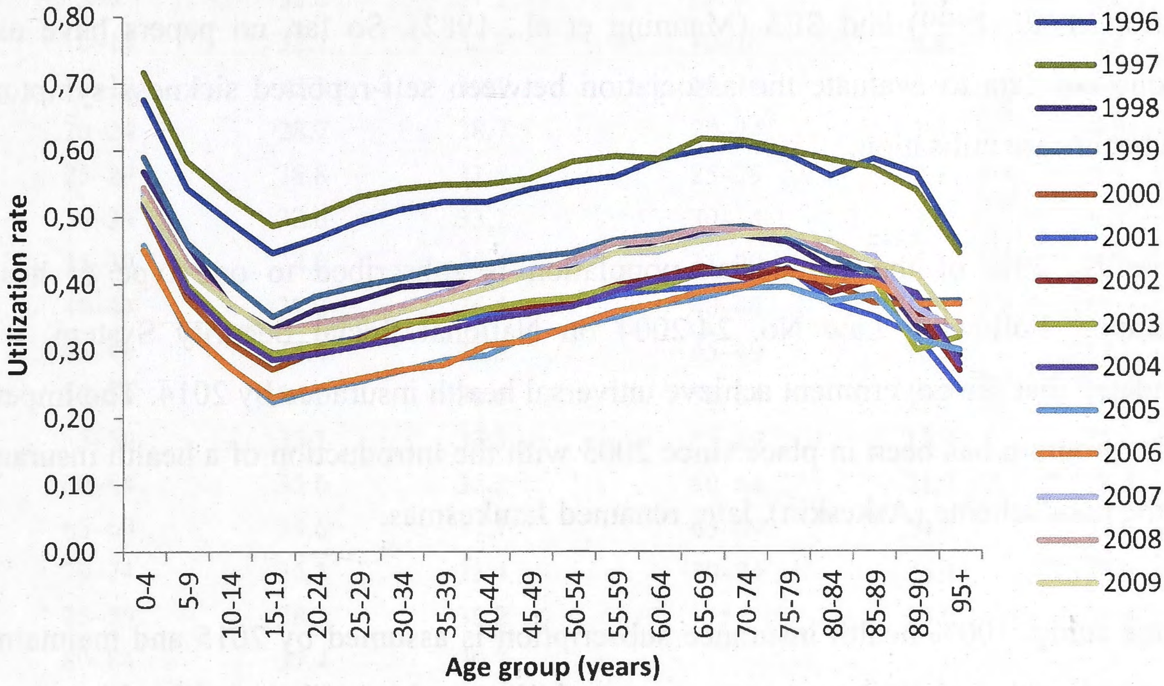
	Probability of utilisation when sick					Probability of utilisation			
	Male		Female			Male		Female	
Age group	Insured	Not Insured	Insured	Not Insured	Age group	Chronic Disease	No-Chronic Disease	Chronic Disease	No-Chronic Disease
0–4	0.592	0.512	0.606	0.526	0–4	0.494	0.412	0.530	0.405
5–9	0.476	0.396	0.490	0.410	5–9	0.485	0.341	0.500	0.339
10–14	0.417	0.341	0.431	0.354	10–14	0.454	0.272	0.463	0.270
15–19	0.369	0.297	0.383	0.309	15–19	0.463	0.224	0.511	0.256
20–24	0.385	0.311	0.398	0.323	20–24	0.467	0.222	0.571	0.311
25–29	0.397	0.322	0.410	0.335	25–29	0.500	0.248	0.575	0.342
30–34	0.412	0.336	0.426	0.349	30–34	0.536	0.275	0.611	0.354
35–39	0.431	0.353	0.445	0.367	35–39	0.564	0.299	0.619	0.357
40–44	0.447	0.368	0.461	0.382	40–44	0.609	0.317	0.644	0.365
45–49	0.464	0.385	0.479	0.399	45–49	0.625	0.325	0.664	0.376
50–54	0.475	0.395	0.489	0.409	50–54	0.640	0.341	0.688	0.402
55–59	0.490	0.410	0.504	0.424	55–59	0.657	0.360	0.681	0.398
60–64	0.490	0.410	0.504	0.424	60–64	0.669	0.381	0.703	0.409
65–69	0.510	0.429	0.524	0.443	65–69	0.698	0.417	0.711	0.420
70–74	0.518	0.437	0.532	0.451	70–74	0.697	0.434	0.690	0.452
75–79	0.518	0.437	0.532	0.451	75+	0.683	0.429	0.657	0.425
80–84	0.492	0.411	0.506	0.425					
85–89	0.487	0.407	0.501	0.421					
90–95	0.408	0.333	0.422	0.346					
95+	0.373	0.301	0.387	0.313					

Notes: Estimated with logistic regression with following independent variable: sex, age group, health insurance subscription status or chronic disease status.

In each projection year, probability of utilisation (p) is assumed constant over time, using the probability from 2007. That is, for an individual of a certain age and sex, the probability of visiting healthcare by insurance or chronic disease status remains the same as in 2007. The stability of p is necessary to evaluate the pure effects of sex, age and insurance or chronic disease status. This study also assumes the stability of the pattern p across age and sex of the sample.

This stability of pattern is evident from utilisation data from multiple rounds of Susenas (see Figure 8.2). The figure clearly shows a 'sleeping S' curve for all Susenas years, indicating the stability of the pattern of utilisation. The curves, however, shift upward or downward across years, indicating that whatever the cause of this shift, it affects utilisation for all ages by the same magnitude. Chapter 4 has analysed the association of the utilisation with various determinants, which could potentially change both the pattern and level of this utilisation curve. In this chapter, health insurance and chronic diseases are chosen as an example.

Figure 8.2 Pattern of healthcare utilisation by age in Indonesia 1996–2009



The sickness rate is required to estimate the effect of demographic and health insurance subscription for the total ill population in 2007. The sick rate is necessary since the question on health insurance subscription in 2007 Susenas is asked only to those who are ill (that is, those who have developed at least one of the sickness symptoms listed in the questionnaire). Although a previous study by Hidayat (2008), using 1997 IFLS data, shows that the exclusion of those who are not sick from the model does not cause selection bias, in this study no attempt will be made to draw conclusions for the general population by including those who are not sick.

The sickness rate throughout the duration of the projection is assumed constant at 2007 levels. Again, this stability of the sickness rate is assumed to isolate as much as possible the effects on future utilisation of age, sex and health insurance and chronic disease status. The consequence of the stable sickness rate is that projected utilisation is either underestimated or overestimated, depending on the trend of the sickness rate in the future. However, the comparison of the effects of demographic and non-demographic characteristics may not be affected by the sickness rate.

Another reason to keep the sickness rate constant is that sickness rate is measured with self-reported sickness. While this is a valid measure of the general health status of an individual (Fosse and Haas, 2009, Miilunpalo et al., 1997), self-reported sickness can introduce bias and reporting errors, which are influenced by the most recent visit (Sutton et al., 1999) and SES (Manning et al., 1982). So far, no papers have used Indonesian data to evaluate the association between self-reported sickness symptoms and healthcare utilisation.

Currently, 29% of the Indonesian population is subscribed to one type of health insurance. Following Law No. 24/2004 on National Social Security System, it is mandated that the government achieve universal health insurance by 2014. The impetus of the program has been in place since 2005 with the introduction of a health insurance for the poor scheme (Askeskin), later renamed Jamkesmas.

In this study, 100% health insurance subscription is assumed by 2015 and maintained afterward. Although the target seems very ambitious and is unlikely to be achieved, it is important to assess the effects of this policy, to allow for discussion of measures that might be included in future planning to anticipate the effects to increased healthcare utilisation. As the starting point for the healthcare insurance subscription rate (the proportion of population with insurance in 2007) is not similar for all age and sex categories, the speed of increase in subscription will be different for each group. The fastest growth is among children, who, in 2007, had the lowest subscription rate.

Assessing the effects of health insurance is not an easy task. As has been explained in Chapter 4, there are at least four categories of health insurance subscription status: not insured, Askes, Askeskin and Private insurance. Each of these have different effects on healthcare utilisation. In this model, to simplify the interpretation, health insurance will be collapsed into two categories; that is, not insured (71% of the population) and insured (a collapsed category of Askeskin, Askes and Private, which accounts for 29% of the population). Chapters 4 and 5 have discussed that the simplification of the insurance category will likely not affect overall healthcare utilisation.

Table 8.3 The prevalence of health insurance and chronic disease rate 2007, by age and sex

Age group	Health insurance (%)		Age group	Chronic disease (%)	
	Male	Female		Male	Female
0–4	25.9	25.5	0–4	0.3	0.3
5–9	32.0	31.1	5–9	0.3	0.4
10–14	32.7	32.2	10–14	0.4	0.4
15–19	32.1	30.1	15–19	0.9	1.1
20–24	28.7	28.7	20–24	1.3	2.0
25–29	28.8	31.8	25–29	2.1	3.1
30–34	32.0	33.2	30–34	3.6	5.3
35–39	34.0	36.4	35–39	5.2	8.9
40–44	37.0	36.4	40–44	7.8	13.0
45–49	36.4	36.2	45–49	10.8	17.1
50–54	36.2	36.6	50–54	14.7	22.8
55–59	35.1	37.3	55–59	17.9	25.2
60–64	35.6	38.2	60–64	21.7	28.4
65–69	39.6	37.7	65–69	24.6	31.6
70–74	36.3	35.4	70–74	26.4	32.6
75–79	38.3	36.2	75+	28.0	31.6
80–84	37.4	30.7			
85–89	33.9	32.4			
90–94	31.7	26.6			
95+	28.4	25.2			
Total	**32.7**	**32.9**		**4.9**	**6.8**

Data sources: Prevalence of health insurance is calculated from 2007 Susenas, and chronic disease is from 2007 Riskesdas

Information on the chronic disease rate is available in 2007 Riskesdas. Since it is not possible to isolate chronic disease prevalence for those who are sick (like in 2007 Susenas); rather, the projection of healthcare utilisation in Riskesdas applies to the whole population sample, not only those who are sick.

Although it is known with a high degree of certainty that the prevalence of chronic disease in Indonesia is increasing, the speed of this increase is not known. In this model, prevalence of chronic diseases is assumed to increase at 0.5 percentage points annually. This increase is then standardised by age group. This chronic disease trend is borrowed from the increase rate of hypertension in South Asia. This increase is assumed to occur among all age groups at a constant proportion annually.

D. Projected Healthcare Utilisation

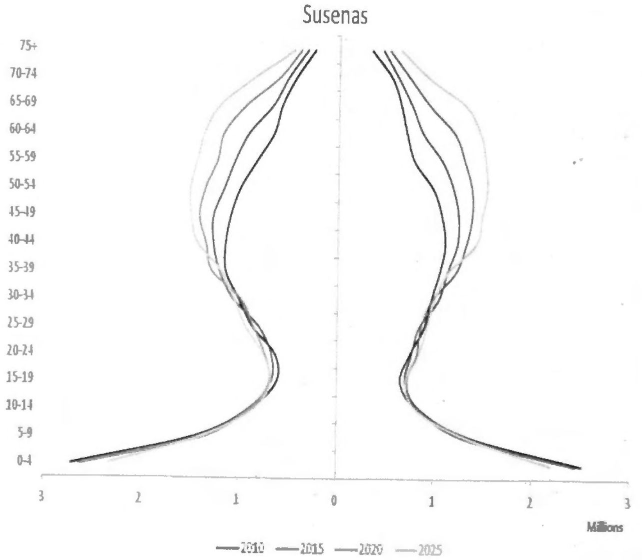
D.1. Rate of Utilisation

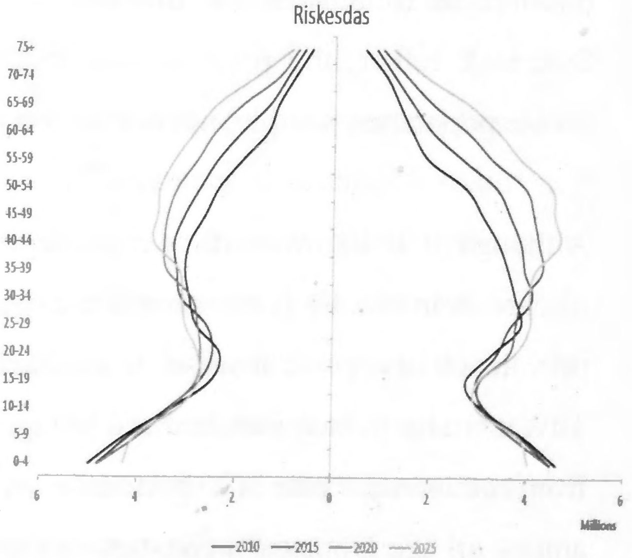
D.1.1. Demographic Effects

Using data from the 2007 Susenas as the baseline, it was estimated that by 2010 there would be 32.8 million visits to healthcare providers by the population who reported as experiencing illness (about one-third of the total population) in the last one month, shared equally between males and females. Utilisation among children (age 0–4) was highest (5.4 million visits), accounting for 16.4% of total utilisation in that year. Utilisation then decreased with age until 15–19, before rising again to peak at age 35–39, to then begin the irreversible decline in utilisation heading towards old age.

Between 2010 and 2025, total population is projected to increase by 16%. The combination of decline in fertility and mortality rate causes the number of births to decline and the number of adolescents, adults and the elderly to increase. With this change, the total level of utilisation is projected to increase by 25%. The utilisation grows following the change of population size. The level of utilisation among children 0–14 decreases (-7.2%), while the level of utilisation of the cohorts aged 15–64 and age 65+ increases by 32.2% and 84.3%, respectively.

Figure 8.3 Projected healthcare utilisation pyramid 2010–2025 for ill population (Susenas) and for all population (Riskesdas)



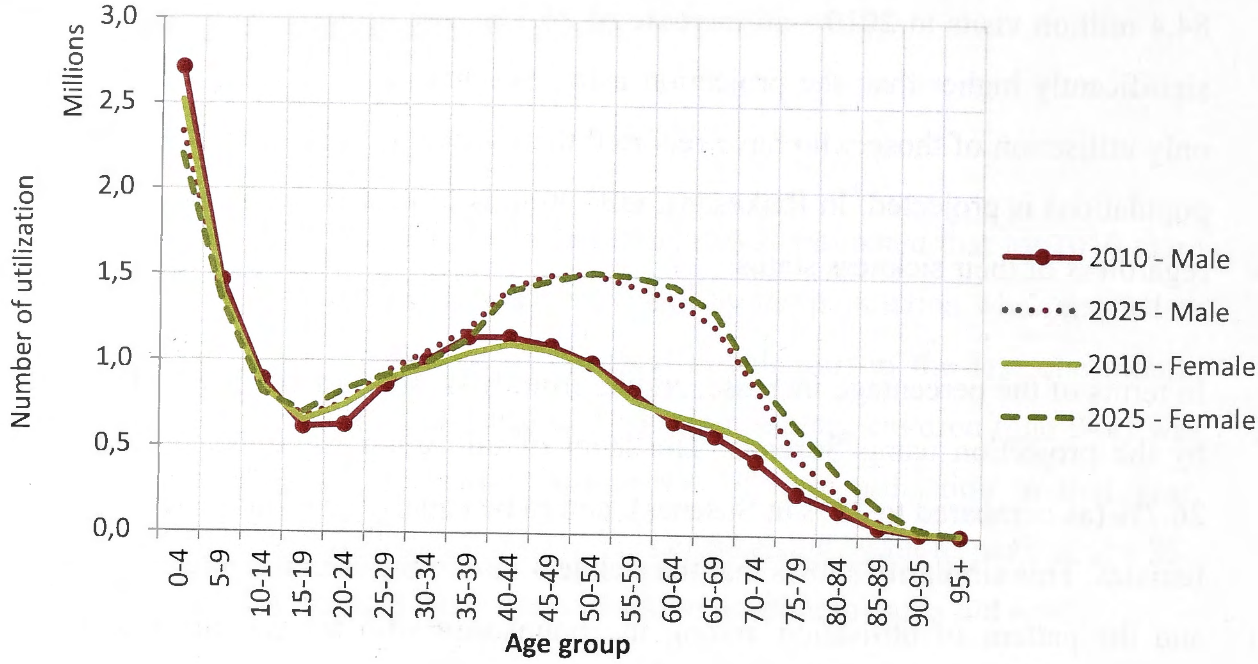


Using Riskesdas data, the utilisation in 2025 is projected to increase to 103 million from 84.4 million visits in 2010—an increase of 26.7%. The projected utilisation in 2025 is significantly higher than the projection using Susenas data (32.8 million). In Susenas, only utilisation of those who have reported themselves as sick (about one-third of total population) is projected. In Riskesdas, utilisation is projected for the whole population, regardless of their sickness status.

In terms of the percentage increase, results from Riskesdas are similar to those returned by the projection using Susenas. The level of utilisation is projected to increase by 26.7% (as compared to 25% in Susenas), and to be equally distributed among males and females. This similarity shows that the sickness rate in Susenas and Riskesdas is similar, and the pattern of utilisation among the population who are not reported as sick in Susenas is not very different from the pattern recorded for the sick population. This result also confirms the findings of a previous study by Hidayat (2008), who showed that there is no selection bias in the utilisation of healthcare due to the conditionality of illness.

Figure 8.4 shows the likely level of utilisation in 2010 and in 2025 among males and females because of demographic changes, projected using Susenas data. Using Riskesdas data, the projection resulted in a similar pattern of changes, and thus that result is not presented here. In general, the utilisation across age groups among males and females fluctuates in a similar pattern (sleeping S-curve pattern). The increase of utilisation primarily occurs among the 40–44 year age group and above, while among the youngest cohort of the population, utilisation declines. Among the elderly (65+), the level at which people will want to utilise healthcare services is expected to increase by only 3.0 million, as compared to adult (aged 15–64) usage, at 5.9 million visits.

Figure 8.4 Projected utilisation by age group and sex, 2010 and 2025



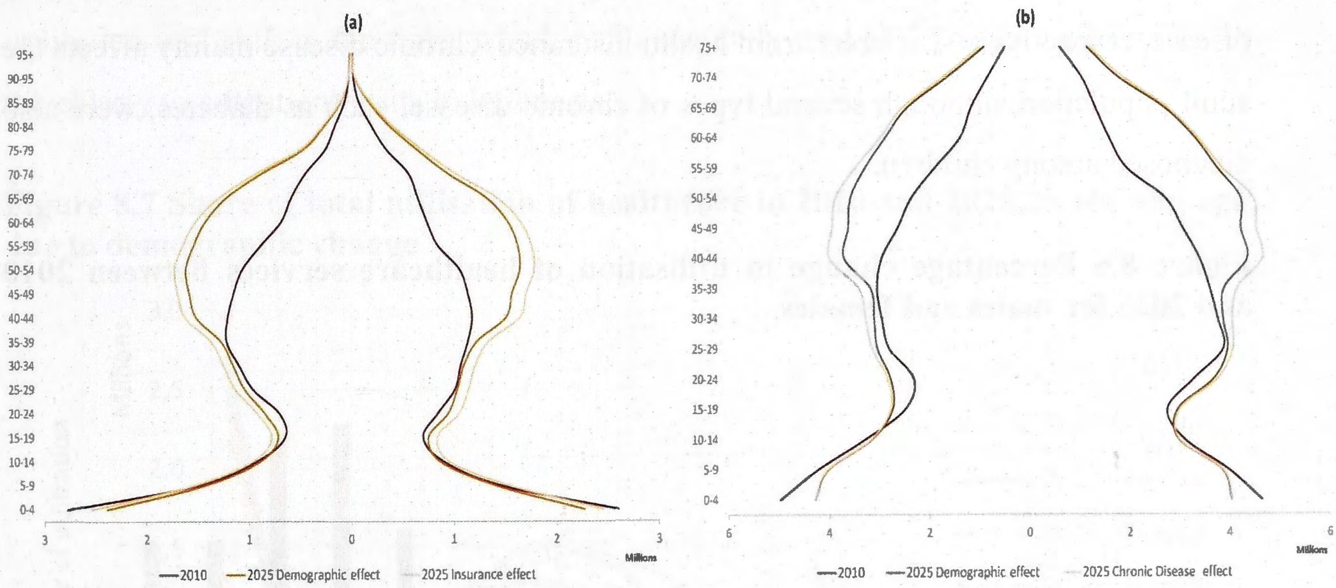
Compared to adult males, adult females are set to use healthcare services at a slightly higher level (2.9 million for males and 3.0 million for females). However, among the elderly, the increase in utilisation among females (1.6 million) will be much higher than among males (1.4 million). In 2010, although utilisation by males in the 50–54 and 55–59 age groups was higher, the greater growth in the female population means that females' utilisation in 2025 is likely to exceed that of males.

D.1.2. The Effects of Health Insurance and Chronic Disease

The effect of health insurance can be evaluated by comparing the change of utilisation in two hypothetical populations; that is, a population with a constant health insurance rate and a population with an increased health insurance rate. Similarly, to evaluate the effect of chronic diseases, utilisation among the population with a constant chronic disease rate is compared with a population with an increased rate of chronic disease. In the population with a constant health insurance and chronic disease rate, the cause of future utilisation is the change in size and structure of the population. In this chapter, this is referred to as the 'demographic effect'.

Figure 8.5 (a) presents the pyramid of projected utilisation in the baseline population (2010 graph), a population with a constant health insurance rate in 2025 (2025 demographic effects) and a population with increased health insurance rate in 2025 (2025 insurance effects). Figure 8.5 (b) presents the baseline utilisation, demographic effects and chronic disease effects, projected using Riskesdas data.

Figure 8.5 Pyramid of projected utilisation 2010 and 2025 comparing demographic effects, insurance effect and chronic disease effects



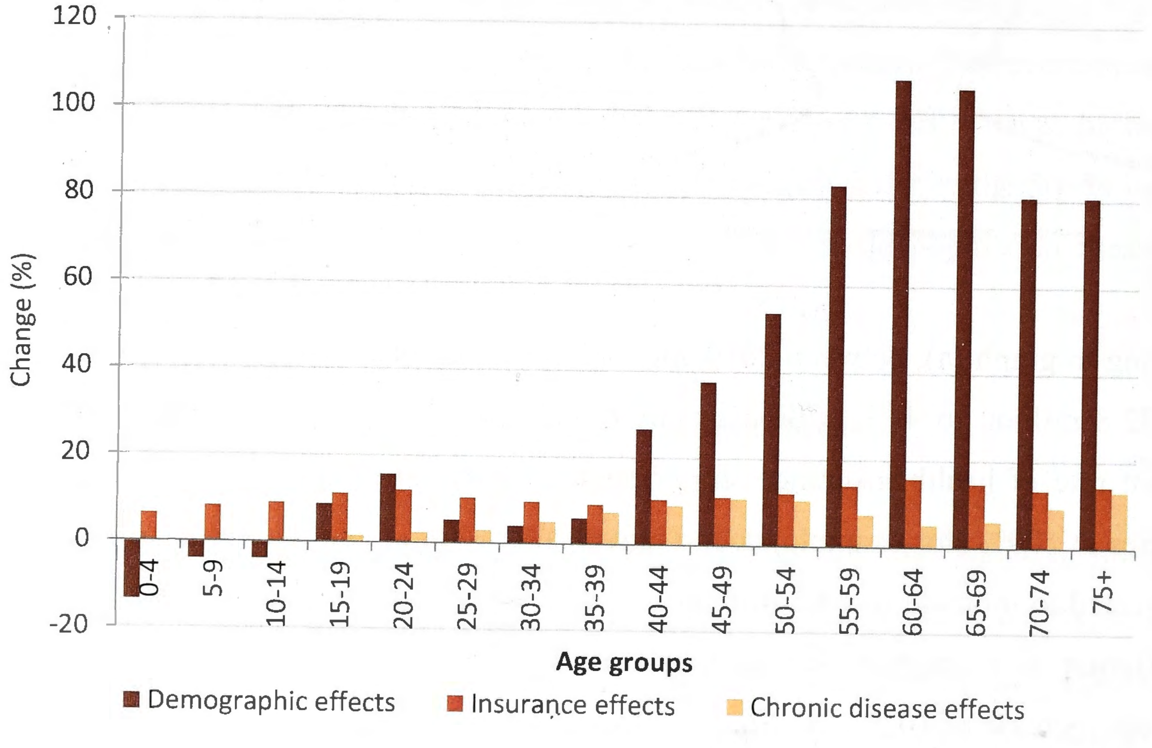
Referring to graph (a), between 2010 and 2025, total utilisation is projected to increase from 32.8 million to 41.2 million in one month, due to increased population, with a constant rate of health insurance subscription (29%). If health insurance subscription increases to 100% (for example, due to universal coverage), the total level of utilisation is projected to increase to 44.6 million. In other words, an increase in health insurance subscription of more than threefold will result in an addition 3.4 million healthcare visits (an increase of 10.5% in utilisation from 2010).

Similar calculations can be made to evaluate the effect of increased chronic disease rate (graph (b)). An average increase of chronic disease rate from 6.8% to 14.3% in 2025 (that is, an increase of 0.5 percentage points per annum) will add 4.7% to total utilisation by that same year. A summary of the effects of demographics, health insurance and chronic disease on future utilisation is presented in Figure 8.5.

The effect of demographic change varies considerably between age groups. Compared to 2010, utilisation in 2025 decreases by 3.9% for age group 10–14, but increases by 107.8% for age group 60–64. This variation is attributable to the decline in TFR, and the increase cohorts of adults and the elderly.

The effect of health insurance and chronic disease are positive and less varied. The changes in utilisation between 2010 and 2025 vary from 0.1% (age 0–4) to 15.9% (age 64–65) and from 0.1% (age 0–4) to 13.1 (age 75+) for health insurance and chronic disease, respectively. Different from health insurance, chronic disease mainly affects the adult population, although several types of chronic disease, such as diabetes, were also diagnosed among children.

Figure 8.6 Percentage change in utilisation of healthcare services between 2010 and 2025 for males and females

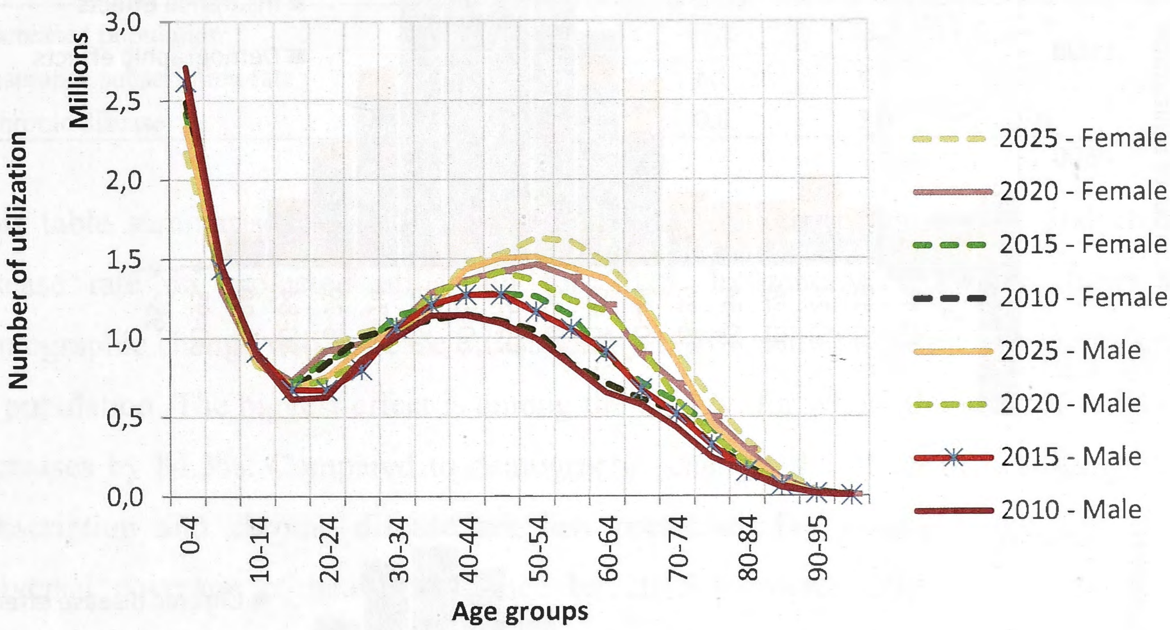


The utilisation of healthcare increases by 9.3% and 11.6% among males and females, respectively, due to health insurance effects. However, the increase in the utilisation due to increased chronic diseases is higher among males (5.1%) than among females (4.1%). This is primarily due to a larger increase in the proportion of male population than female population, particularly for the ages 10–30 years and 60 years and above during the projection periods.

Figure 8.6 also shows that the change in utilisation between 2010 and 2025 due to demographic shifts for ages 35-39 and 40-44 is quite distinctive. The increase in utilisation by 40–44-year olds is driven by the bulk of Indonesians alive today having been born between 1985 and 1990, as enumerated in the 2010 census.[38]

The effects of demographic change are presented in Figure 8.7. The biggest contributor to the total increase in rate of utilisation is the population group aged 40 and above. Since this trend will continue, following the demographic change, the share of utilisation will shift to the right, which will eventually lead to a greater contribution by the elderly to outpatient visits in Indonesia.

Figure 8.7 Share of total utilisation of healthcare in 2010 and 2025 by sex and age, due to demographic change

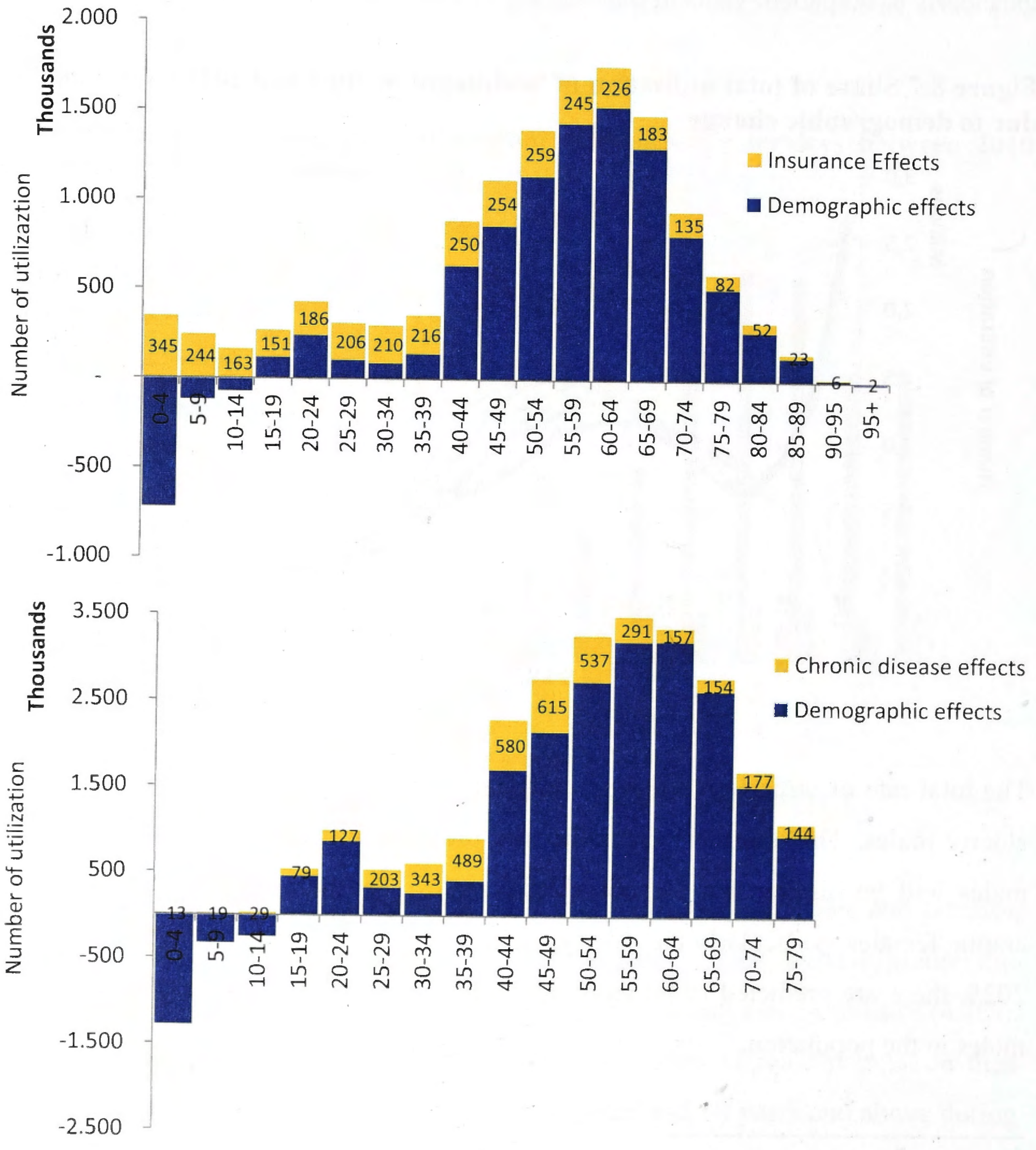


The total rate of utilisation among elderly females in 2025 will be higher than among elderly males. This does not contradict the probability that utilisation among elderly males will be higher than for non-elderly males. The higher number of utilisations among females, particularly the elderly, is driven by an increasing female population. In 2025, there are predicted to be more adult and elderly females than adult and elderly males in the population.

[38] There is a potential inconsistency between the 2000 and 2010 Census data, shown by an increase in the size of a certain age cohort in 2010. Although, this could be a result of positive net international migration of that particular age (which is unlikely), or an under enumeration in the 2000 census. At the time of writing this report, there is no conclusive explanation for this.

Analysis of each group reveals that the contribution of health insurance can be greater than the demographic effects. For example, among children, increased utilisation due to insurance can balance out the negative effects on utilisation of demographic factors. The effect of insurance is particularly pronounced among ages 0 to 39 years. The effect of chronic diseases, on the other hand, is more profound among the early and middle adulthood, with little or no effect among children.

Figure 8.8 The change in rate of utilisation between 2010 and 2025, due to demographic changes and health insurance subscription rate



Comparison on the effects of demographic, health insurance and chronic disease on utilisation can also be performed for the three groups of population: children (age 0–14), adults or the economically active population (age 15–64) and the elderly (65+). As the base of the population is not the same as for the utilisation projection (Susenas for health insurance effect, and Riskesdas for chronic disease effect), direct comparison between the effect of health insurance and chronic disease is conducted using relative change in percentage (Details of percentages of change in utilisation by age are provided in Appendix 15). The result of the comparison is provided at Table 8.4.

Table 8.4 Effects of demographic, health insurance and chronic disease changes on the rate of utilisation 2010–2025

Determinants	Change in determinants 2010–2025 (%)	Change in utilisation (%) 2010–2025			
		Children (0–14)	Adult (15–64)	Elderly (65+)	All age
Increased population	16	-7.2	32.2	84.3	19.6
Insurance subscription rate	245	8.1	8.1	7.5	10.5
Chronic disease	110	0.0	5.0	5.0	4.7

This table summarises the effect of demographic, health insurance rate and chronic disease rate on projected utilisation for 2025. In general, the table shows that demographic change will increase utilisation by 19.6%, with the result varying by group of population. The biggest effect is among the elderly, for whom the level of utilisation increases by 84.3%. Compared to demographic change, the effect of health insurance subscription and chronic disease are less profound. For example, the aim of for universal coverage of health insurance by 2015 increases outpatient utilisation by 10.5%, while an increase in chronic disease rate of up to 110% increases utilisation by 4.7%.

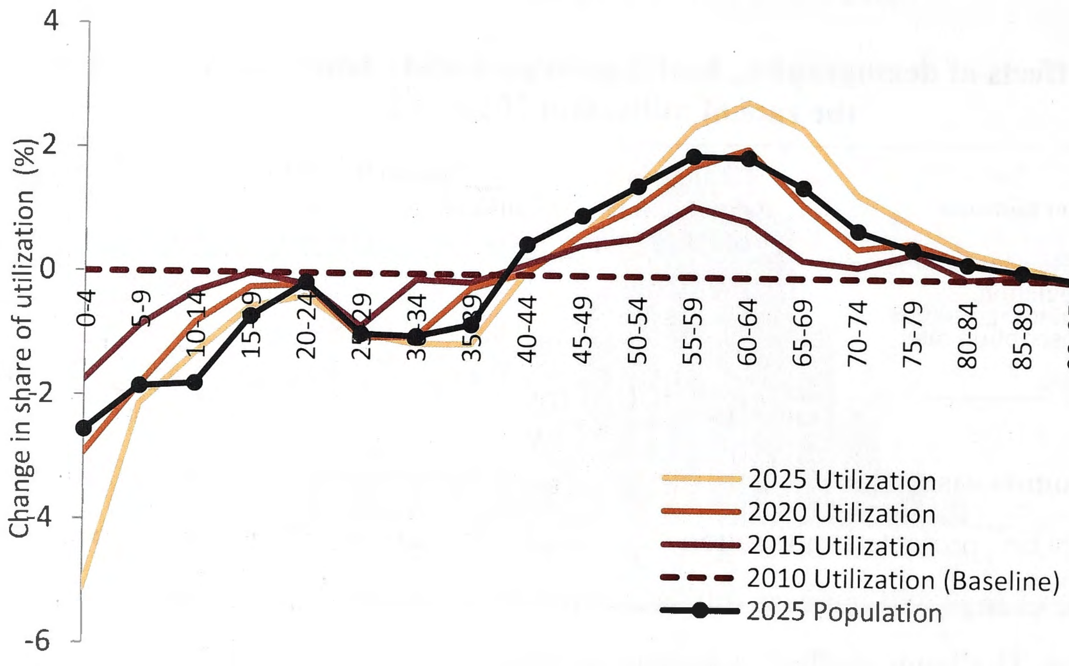
D.2. Pattern of Utilisation

D.2.1. Demographic Effects

In addition to the rate of utilisation, demographic and non-demographic factors can also affect patterns of utilisation by sex or age group of population. Pattern of utilisation in this regard is the share or contribution to utilisation (usually measured by proportion or percentage) of a certain population group to the total utilisation in the same year. In this study, the pattern will be compared between males and females, and among age groups of population.

The effect of demographic change is straightforward. Since for each sex and age group the only change between 2010 and 2025 is the size of the population, the change of utilisation follows the change in pattern of population by age and sex.

Figure 8.9 The change in the share of utilisation between 2010 and 2025, by age group



Due to decreased number of births during the projection period, the share of utilisation among children also decreases over time. Compared to 2010, the share of utilisation among children aged 0–4 years in 2015, 2020 and 2025 decreases continuously by 1.8%, 3.0% and 5.2%, respectively. Other age groups will experience an increase of utilisation due to their having an increased share in the population. For example, the utilisation for age group 60–64 years is expected to increase by 0.3%, 1.2% and 3.8% in 2015, 2020 and 2025, respectively.

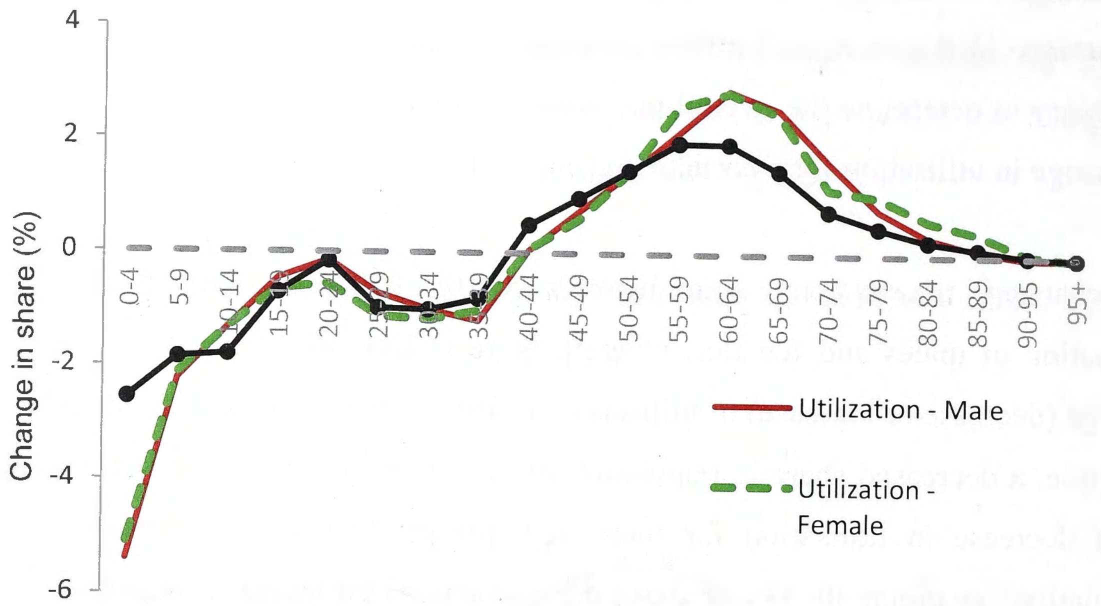
Overall, a decrease in the share of utilisation of healthcare is likely to occur among the cohort aged 0 to 39 years. Those aged 40 and above, on the other hand, can expect an increased share in utilisation. In 2025, the highest decrease in share of utilisation is to occur among the age group 0–4 (-5.2%); while the highest increase is expected for those aged 60–64 years (2.8%).

The analysis of change in shares is particularly important to provide weight or degree of importance in the change of utilisation from the national perspective. This measure is necessary to determine the overall magnitude of the changes, by considering the extent of change in utilisation for a particular group and size of the population.

The change in the sex composition between 2010 and 2025 is reflected in the pattern of utilisation of males and females. Overall, there is little difference in the direction of change (decrease or increase) of utilisation. It follows the changes in the population. For example, a decreased share in population of age group 0–4 to 35–39 years is followed by a decrease in utilisation for these age groups. Further, the increased share of population age group 40–44 and above drives the need for increased shares of utilisation among adults and the elderly.

Compared to the change in the age structure of the population, the pattern of utilisation is quite similar in the direction of change to the pattern of population size. The difference in the magnitude is more obvious, especially among children, late adults and the elderly. Among children aged 0–4, the decrease in share of utilisation is almost double the decrease in their share of population size. At the other end of the spectrum, a similar phenomenon occurs, but in an opposite direction, whereby an increase in utilisation exceeds the increase in the population. The combination of decrease among children and increase among adults and the elderly in the long run, can potentially shape the pyramid of utilisation into a coffin shape utilisation pyramid at a faster rate than the change in shape in population pyramid.

Figure 8.10 The change in the share of utilisation 2010 and 2025, by sex and age group



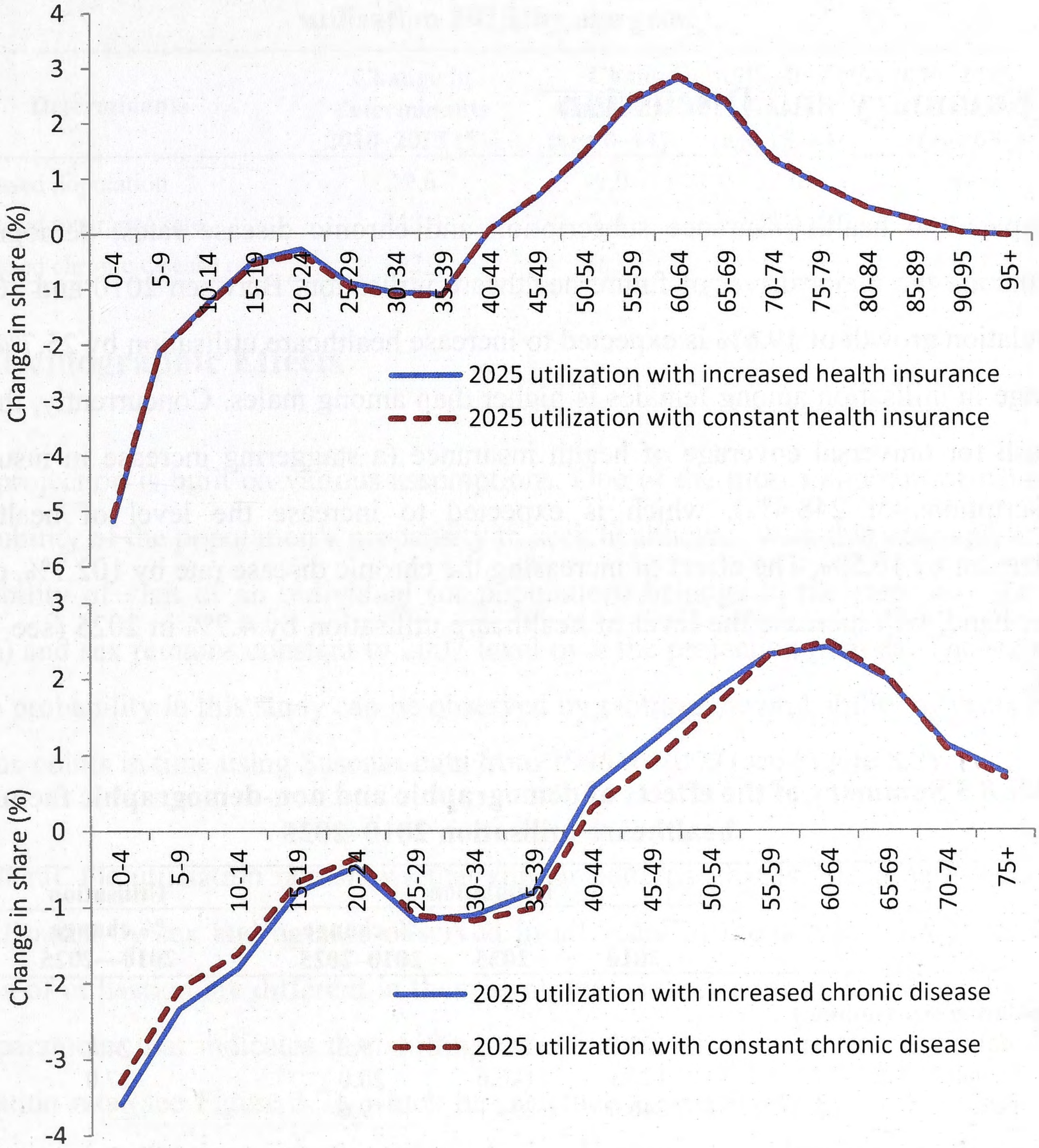
There is a slight difference between males and female in terms of magnitude of the changes, especially among the elderly. Figure 8.10 shows that the change in the proportion of utilisation for older women is higher than for males. This is an indication that in the future, utilisation among the elderly female population will grow faster than for males.

D.2.2. Health Insurance and Chronic Disease Effects

In Figure 8.11, the graph of healthcare utilisation with a constant health insurance rate implies the absence of universal health coverage in 2025. This line is actually showing the effect of demographic change as the sole driver of utilisation. Another line indicates the utilisation in 2025, after taking universal coverage of insurance into account. Therefore, the gap between these two graphs reflects the effect of health insurance.

In this graph, the change in utilisation of the 2025 population with increased health insurance almost fits perfectly with the utilisation due to increased population. In other words, the effect of health insurance in shaping the pattern of healthcare utilisation in the future population is not significant. Although the effect of health insurance does significantly alter the pattern of utilisation, or add to it, the magnitude of the increased utilisation does not alter the overall share of utilisation among the various age groups.

Figure 8.11 Change in population and proportion of utilisation by age groups, between 2010 (baseline) and 2025



For people that have been diagnosed with at least one type of chronic disease, the probability of visiting a healthcare provider is higher and not uniform across age. Consequently, in addition to increasing the utilisation levels of the future population, an increased chronic disease rate can potentially change the pattern of utilisation by age group. The gain in increased utilisation due to chronic diseases among children is outweighed by a decrease in the number of children overall, resulting in a decreased share of utilisation for children. Among adults aged 30–60, the combination of higher probability of visit among adults diagnosed with chronic disease and a growing population increases the share of utilisation at these ages. Increased chronic diseases, especially among the elderly, will not increase the share of elderly utilisation to total utilisation healthcare, since it is undermined by the higher increase utilisation among adults.

E. Summary and Discussion

Compared to health insurance subscription and chronic disease rates, demographic factors are the major driver of future healthcare utilisation. Between 2010 and 2025, a population growth of 19.6% is expected to increase healthcare utilisation by 25.7%. The change in utilisation among females is higher than among males. Concurrently, there is a push for universal coverage of health insurance (a staggering increase in insurance subscriptions of 248.4%), which is expected to increase the level of healthcare utilization by 10.5%. The effect of increasing the chronic disease rate by 102.7%, on the other hand, will increase the level of healthcare utilisation by 4.7% in 2025 (see Table 8.5).

Table 8.5 Summary of the effects of demographic and non-demographic factors on healthcare utilisation 2010–2025

	Population			Utilisation
	2010	2025	% change 2010–2025	% change 2010—2025
Population size (million)				
Male	123.8	147.5	19.2	24.4
Female	122.1	146.6	20.0	27.0
Total	246.0	294.1	19.6	25.7
Health Insurance rate (%)				
Male	28.5	100.0	250.9	9.3
Female	28.9	100.0	246.0	11.6
Total	28.7	100.0	248.4	10.5
Chronic Disease rate (%)				
Male	6.4	13.9	117.2	5.3
Female	8.3	15.8	90.4	4.1
Total	7.3	14.8	102.7	4.7

In terms of pattern of utilisation, the effects of both demographic and non-demographic factors (in this case, health insurance subscription and chronic disease rate) are more profound among the elderly, followed by adults and then children. The decrease in utilisation among children due to declining fertility rate can be balanced out by positive effects of health insurance.

Table 8.6 Summary of the effects of demographic and non-demographic factors on utilisation 2025, by age group

Determinants	Change in determinants 2010–2025 (%)	Change in utilisation (%) 2010–2025		
		Children (age 0–14)	Adult (age 15–64)	Elderly (age 65+)
Increased population	19.6	-9.0	32.6	89.9
Increased insurance rate	248.4	7.4	11.4	14.3
Increased chronic disease rate	102.7	0.2	6.2	8.7

E.1. Demographic Effects

This projection is built on various assumptions. One of the most important of which is the stability of the population's propensity to seek healthcare. With this assumption, the probability of visit of an individual (or population) belongs to the same age (or age group) and sex remains constant to 2007 level over the projection periods. The stability of the probability in this study can be observed by plotting the probability of visits from various points in time using Susenas data from 1996 to 2009 (see Figure 8.2).

In general, the utilisation rate shows that similar patterns (that is, Sleeping S—curves) of utilisation by sex and age are observed in all years of the survey. However, these graphs of utilisation are different in their level; that is, they shift up and down by year. One parameter that indicates this shifting of overall level of utilisation is the national utilisation rate (see Figure 3.7), which has fluctuated extensively in the last decade. If the national utilisation rate increases, the probability of visiting healthcare might increase for all ages and sexes. The opposite is also true.

As in Chapter 4, both demographic and non-demographic factors, such as marital status, education and household income level, are influential in determining the level of utilisation of healthcare. If level of these factors were not assumed constant, the probability of visiting by sex and age may not have been stable, and thus would have led to different levels of utilisation of healthcare. To assure the stability of the model, the probability of utilisation is decomposed by sex and age group only (and later by health insurance and chronic disease status, when inspecting the effects of non-demographic factors).

Several potential variables that may influence the probability of visits, but which are not taken into account in this chapter include increasing household income and women's education level. The probability of visiting for women in the next 15 years is expected to be higher due to increased income and education from the baseline (refer to Table 4.4 in Chapter 4 for a discussion of the increased probability of healthcare utilisation due to increased SES). Subsequently, the increase in the female population will increase utilisation higher than the level currently projected for the model.

A more complex model can be developed to incorporate further the various demographic and non-demographic factors, so that it is possible to project or even forecast future utilisation with a higher degree of accuracy. However, using a propensity model with many variables is very complex and involves many assumptions that are difficult to verify. Another possible approach is incorporating uncertainties into the model, so that the utilisation is projected stochastically. The level of uncertainty can be obtained from variations of probability of utilisation caused by demographic and non-demographic variables of interest.

Neither of these approaches is pursued in this study. The objective was not to produce accurate forecasts of future utilisation, but rather to provide a comparison of the effects of demographic and non-demographic factors, with health insurance and the chronic disease rate as examples. For that purpose, the propensity model by decomposing the probability of visit by sex, age, health insurance status and chronic disease status was sufficient. However, additional variables can be added to the model if necessary.

E.2. Health Insurance Effect

The purpose of health insurance is to reduce the out of pocket expenditure for healthcare service (Feldstein, 2011, Phelps, 1997, Zweifel and Manning, 2000). In relation to prediction, it is well accepted that insurance is likely to increase healthcare utilisation (Buchmueller et al., 2005). In this study, health insurance subscription is associated with increased healthcare utilisation (see Chapter 4). This finding supports previous studies on the role of health insurance in Indonesia (Hidayat et al., 2004, Rokx et al., 2010, Sparrow et al., 2010).

Simulating the universal coverage of health insurance resulted in an increase of 10.5% in total utilisation, which is less than the increase due to demographic changes. The notion of moral hazard (that is, the unnecessary use of health insurance) may also lead to a perception that the effect of health insurance should not have been so small. However, comparing other studies and the results of this study, the magnitude of this effect is quite comparable. In this study, according to 2007 Susenas data, being subscribed to health insurance (any type) increases the probability of utilising healthcare by 0.075. A study by Sparrow et al. (2010) using 2005 and 2006 Susenas panel data found that Askeskin (a type of health insurance for the poor provided by the government) increased outpatient service utilisation by 0.048 visits per person per month (other types of health insurances were not included in this model, primarily due to the limited number of cases in the survey).

Projecting the effect of increased insurance means calculating the probability of visiting healthcare as a result of individuals having changed their health insurance status. This study uses cross-sectional data as an approximation. Therefore, the association found in this study is not the direct result of switching status from uninsured to insured, but rather a reflection of the differences in utilisation among different population groups; that is, populations with health insurance and population without health insurance. Although not directly comparable, using cross-sectional data resulted in an almost similar magnitude of effect with panel data. In the absence of longitudinal data, various studies on the effect of health insurance on healthcare utilisation have used cross-sectional data (Card et al., 2004, Holl et al., 2000).

There are several important methodological considerations in forecasting or projecting the effect of health insurance; namely, selection bias and unobserved heterogeneity, change in response from the supply side, and the effects of various types of health insurance (Buchmueller et al., 2005).

Predicting the effect of insurance on healthcare utilisation is subjected to the heterogeneity from various sources such as income level, type of health insurance and access to care. From the supply side, any increase in the rate of health insurance may change the behaviour and responses of providers, which eventually affects utilisation, such as in terms of moral hazard (Aron-Dine et al., 2012, Carlsen and Grytten, 2000), supply-induced demand (Pauly, 1994, 1974) and administrative system (Enterline, McDonald et al., 1973, Enterline, Salter et al., 1973).

The grouping of health insurance into a dichotomous variable may undermine the role of each type of health insurance. As each type of health insurance is specific in terms of target beneficiaries and in the preferred providers, the effect could be more profound if each is measured as a type of healthcare provider. For example, an increase in private health insurance might boost the use of private providers; whereas increased health insurance might drive the utilisation of public providers, and so forth. This study uses data utilisation conditional to sickness and thus reduces the selection bias of health insurance. Insignificant selection bias was confirmed by an endogeneity test of health insurance (provided in Chapter 4).

E.3. Effects of Chronic Disease

Chapter 4 has shown that being diagnosed with a chronic disease is significantly associated with increased healthcare utilisation. In the model, the chronic disease variable has the highest standardised coefficient, meaning that it can explain a large proportion of variation in the utilisation model. This result is in line with previous studies (Natarajan and Nietert, 2004, Wolinsky, 1978), which have shown a strong relationship between chronic disease and healthcare utilisation. Healthcare utilisation, and specifically outpatient visits, has a close relationship with chronic disease, since it is used as a way to control adherence when using medication (Bell and Kravitz, 2008) and in health management more generally (Scott et al., 2004).

According to 2007 Riskesdas, a person diagnosed with a chronic disease is on average about two times more likely to seek healthcare than is a person not diagnosed with a chronic disease (see Table 8.1). In addition, in Chapter 4, the model estimated that the odds ratio of visiting a healthcare provider for a person diagnosed with hypertension is 168% higher than for a person without hypertension. A previous study indicated that health need is the immediate causal effect of healthcare utilisation (Wolinsky, 1978), supporting the idea of health need as a direct factor in health service use (Andersen, 1995, Andersen and Newman, 2005).

At the individual level, being diagnosed with a chronic disease can alter healthcare-seeking behaviour significantly. At the population level, however, its contribution to total healthcare utilisation over the next 15 years is projected to be relatively small compared to the effect of health insurance and demographic change. The reason is that the rate of chronic disease is relatively low in the population. With growth in the prevalence of chronic disease over the projection period, the size of the population with a chronic disease will not change significantly relative to total population.

The trend of chronic disease prevalence in the past and into the future is a matter of speculation, as the data on the state of chronic disease over time in Indonesia is very limited. The contribution of non-communicable diseases as the main cause of deaths in Indonesia has increased from 41.7% to 49.9% to 59.5% from 1995 to 2001 and to 2007, respectively (NHRDC, 2007). This is probably driven more by the increased prevalence of chronic diseases, rather than by any deterioration in managing current cases of sickness or by increased reporting.

In the short term, the chronic disease rate is likely to rise. The trend of blood pressure as a risk factor of NCD, for example, continues to increase in most low and middle-income countries (WHO, 2012). In developed countries, blood pressure has been declining since the 1980s. However, a worldwide systematic review on examination surveys and epidemiological studies (Danaei et al., 2011) shows that in Southeast Asia (including Indonesia) blood pressure has been increasing over the last decade for men and women.

In the long term, the trend is more difficult to predict, for it will be significantly influenced by changes in behaviour and life style. It is estimated that behaviour risk factors, such as smoking, alcohol, physical inactivity and unhealthy diet are responsible for 80% of coronary heart disease and cerebrovascular disease (WHO, 2009). Blood pressure is also determined primarily by consumption of salt and vegetables, adiposity and antihypertensive use (Anderson et al., 2010, Elliott et al., 1996). As the behaviour of the population shifts, favouring reduction in risk factors, the trend of chronic disease might be reversed. If this were the case, the effect of chronic diseases on healthcare utilisation would likely be much lower than is projected by this study.

Chapter 9
Policy Implications: Inequity and Quality of Services

One of the motivations of this study was to provide background information for local policymakers working on increasing healthcare utilisation in Indonesia. This chapter discusses some possible implications of the findings for the operation of Indonesia's health system. As previous chapters have shown, use of health service is influenced by demographic, non-demographic and provider characteristics, as well as by their interactions. This chapter explains how these interactions affect various options for policy interventions.

Determinant analysis, both from user and provider perspectives, provides a very rare and valuable insight into decision making relating to healthcare utilisation and choice of provider, and how this will potentially affect the utilisation of the future population. At the very least, this study provides evidence based on empirical data, previously lacking or ignored in the process of planning.

Two main issues are explored in this chapter: equity in healthcare utilisation, and future healthcare utilisation. The containment of exploration into these two issues is a consequence and a continuation of the main findings of this study; namely, the effects of non-demographic, demographic and provider characteristics on healthcare utilisation. The issue of inequity in healthcare utilisation will be based on financial capacity level, while the investigation of the implications for future healthcare utilisation will be based on size and pattern of utilisation.

A. Why Does Inequity in Healthcare Utilisation Matter?

In Indonesia, inequity in health can be seen in the disparity in the outcomes of the health system for different population groups. The IMR among the lowest wealth quintile, for example, is the highest, at 56 deaths per 1,000 live births, while the rate for the highest wealth quintile is the lowest, at 26 deaths per 1,000 live births. Inequity in infant mortality is also observed among the different levels of education and place and island of residence. Population groups with lower educational attainment and living in rural areas have a higher rate of infant mortality (refer to Table 3.1 in Chapter 3 for details). Other indices of health status, such as the maternal mortality rate, also show inequities among different population groups.

Differences in access to healthcare are thought of as a source of health inequity. Theoretically, healthcare is a factor that contributes to health status (Folland et al., 2012) and the inequity of access to healthcare contributes to health inequity. Regional inequity in the total number of medical doctors indicates that medical doctors are more concentrated in Java/Bali and in urban areas. This has led people to believe that access to healthcare for people living outside Java/Bali is much more limited and that poor people are less likely to access healthcare than are the rich.

As previously mentioned, the adequacy of healthcare services is usually measured using health need standards, such as the ratio of medical doctors per 100,000 population and number of health centres per district. Such adequacy measures can be misleading because need does not always translate into demand (Feldstein, 2011). The nature of utilisation is not only determined by the supply side characteristics such as availability of doctors, distance and price, but also by the socio-demographic characteristics of the users (this has been extensively discussed in Chapters 4, 5 and 6). Therefore, it is important to evaluate the inequity in healthcare utilisation; that is, in the actual utilisation of healthcare services, and not only from the supply side perspective.

Several studies have shown the disparities in access to healthcare utilisation in Indonesia (Rokx et al., 2010, Sparrow, 2008). In general, healthcare-seekers from lower income level groups have demonstrated lower utilisation as compared to higher income groups. Using 1997 IFLS, Hidayat et al. (2004) showed that a mandatory health insurance scheme for civil servants (Askes) is positively associated with increased use of public outpatient care, while a mandatory insurance scheme for private employees (Jamsostek) is associated with increased use of public and private outpatient care. There is no evidence, however, that Askes and Jamsostek have positive impacts on equity.

Evaluation on the equity of healthcare utilisation also provides a foundation for the evaluation of healthcare utilisation, especially in assessing the need for health facilities and more health workers in the future. Currently, the practice is to project future need for health facilities and workforce based on the size of the population only. While this approach is simple and straightforward, it is not adjusted for change in population structure (sex and age), and it does not take the variation of utilisation among population groups into account. Misleading projections can resulted in a waste of resources, or worse, in the unmet demand for healthcare services.

B. Concept and Measurement of Inequity in Healthcare Utilisation

There are many definitions of health inequity. The concept and measurement of health inequity has also been reviewed (Braveman, 2006). In a widely cited paper, Whitehead defined health inequities as differences in health that are unnecessary, avoidable and unfair and unjust (Whitehead, 1992). The determinants of health differentials that would be considered avoidable include exposure to unhealthy living conditions and inadequate access to essential healthcare and public services. The resultant differences due to these determinants are considered unjust (Whitehead, 1992).

Equity in health can be measured by health status, resources distribution, expenditure, utilisation and access (Musgrove, 1986). Use of and access to healthcare services have been suggested as indicators of equity in healthcare systems, as they are related concepts and are measured conditional to the need for care (Waters, 2000). This chapter will assess the inequity in healthcare utilisation, particularly outpatient utilisation, but will not assess health status inequity in general.

Whitehead (1992) indicated that there is a distinction between inequity in the level and quality of healthcare, and inequity in the provision and distribution of health services. Equity in healthcare refers to equal access to available care for equal need, equal utilisation for equal need and equal quality of care for all. Equal utilisation for equal need is often referred to as horizontal equity, defined as ‘equal treatment for equal medical need, irrespective of other characteristics such as income, race, place of residence, etc.' (van Doorslaer et al., 2000, Wagstaff and van Doorslaer, 2000).

The difficulty with the concept of horizontal equity is that the definition of 'need' is difficult to interpret and there are various competing criteria to define need (Culyer and Wagstaff, 1993). After elaborative discussion in defining need, Culyer and Wagstaff (1993) proposed that health status offers a better approximation of need. Without simultaneously examining vertical equity, the extent to which horizontal equity is violated is difficult to examine (O'Donnell et al., 2008). O'Donnell et al. suggested that in accessing the differentials by income level, several characteristics could be used as the proxy to 'need', including age, gender and measures of health status. Many studies use 'illness status' as the proxy of need for medical care in studying inequity in healthcare utilisation (Hidayat et al., 2004, Morris et al., 2005, Silver and Stein, 2001, Waters, 2000).

A common method to assess inequity is to construct concentration curves as a visual representation of inequity. The concentration curve plots the cumulative percentage of the health variables (in this case healthcare utilisation) against the cumulative percentage of the population, ranked by income levels. Concentration curves are widely used in the study of health inequity and in other sectors (Doorslaer et al., 1997, Kakwani et al., 1997, O'Donnell et al., 2007, Sahn and Younger, 2000, Wagstaff et al., 1991). Concentration curves can be used to explain inequity among various groups of population. However, they cannot measure the magnitude of inequality across time and location (O'Donnell et al., 2008).

In this study, a concentration index will be used to quantify the degree of inequality in healthcare utilisation, by measuring the extent to which the utilisation line deviates from the equity line on the concentration curve. This measure has also been widely used in studies of health inequity (Gwatkin et al., 2003, Hidayat et al., 2004, Mangalore et al., 2007, Wagstaff et al., 2003).

Formally, the concentration index is defined as:

$$C = \frac{2}{N\mu}\sum_{i=1}^{n} h_i r_i - 1 - \frac{i}{N'} \quad (9.1)$$

Where h_i is the probability of utilising healthcare when sick, μ is its mean and r_i =1/N is the fractional rank of individual i in the income levels, with i=1 for the poorest and i=5 for the richest. The standard errors of the estimator C in the grouped data are computed using the formula given by Kakwani et al. (1997).

The examination of the inequity of healthcare utilisation in this chapter is similar to the probability of utilising healthcare as predicted using logistic and MNL regression as described in Chapters 4 and 5. However, instead of using the 2007 IFLS, the equity analysis uses data from the 2007 Susenas. The Susenas is a national survey covering all provinces and all districts in Indonesia and is nationally more representative than is the IFLS, which covers only 18 out of 33 provinces in Indonesia.

The dependent variable of the model is whether a person is seeking healthcare from any healthcare provider care when sick. The main independent variable is household income quintiles. Subsequently, the term of inequity in this study will refer to inequity between income level groups. Since the analysis is confined to conditionality of sickness, this variable of 'sickness' serves as an approximation of 'need' to ensure equity is measured in populations with the same level of need. A person who has sickness symptoms may have a different need for medical care depending on various factors such as physical development, biological imperatives, psychological condition, the presence of acute or chronic disease and other factors (O'Donnell et al., 2008). Therefore, this 'need' should be standardised. Following practices in previous studies, several covariates are included in the model to standardise need; including sex, age and marital status (for adults and the elderly), household size (number of children in household for children), place of residence (urban or rural) and education levels.

C. Measuring Inequity

The discussion on inequity is presented according to three segments of population, children (aged 0–14 years), adults (aged 15–64 years) and the elderly (aged 65+ years). This distinction is made because the trajectories of healthcare utilisation among these segments are significantly different (see Chapter 4 for details). In addition, from a public policy perspective and within demographic analysis, the categories of children, adults and the elderly are widely used reflecting the different needs for medical care.

Healthcare utilisation (that is, whether people visit healthcare providers when sick) is a combination of records of visits to various healthcare providers, and therefore more variation is expected if the inequity is measured based on the utilisation of each type of provider. MNL regressions are used to explore the inequity of utilisation among the various choices of provider.

C.1. Inequity in Healthcare Utilisation

Inequality assessment on health utilisation requires the comparison of the proportion of sick population among five income quintiles that seek medical care. The model estimates found that income level is associated with healthcare utilisation. This shows an inequity in healthcare utilisation by income level. People from poorer income groups use healthcare less than do people from higher income groups. This is indicated by concentration curves that lie below the equality line (see Figure 9.1.). This inequity occurs for all population groups. In other words, regardless of age, low-income groups have less access to healthcare providers..

To quantify the degree of inequality, concentration indexes (CI) can be calculated (Kakwani et al., 1997, Wagstaff, 1989). The index indicates how large the concentration is. An index with a negative value indicates concentration of healthcare use among the poor and that the curve lies above the line of equality. Conversely, a positive value indicates the concentration of utilisation among the rich and that the curve lies below the equality line (O'Donnell et al., 2007).

Figure 9.1 Concentration curves on the effects of income levels for healthcare utilisation

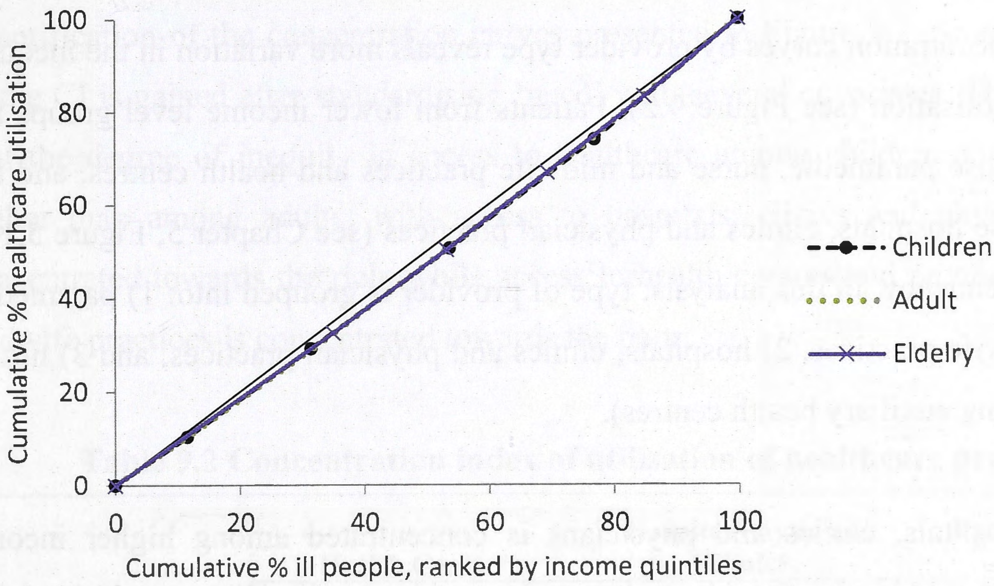


Table 9.1 shows the CI of healthcare utilisation among children, adults and the elderly. All CIs are significantly different from the equity line, with the positive sign indicating inequality, and concentration of use among higher income population groups. The degree of inequity among children, adults and the elderly is almost the same (indicated by the overlaid concentration curves for these three population groups in Figure 9.1).

Table 9.1 Concentration index of healthcare utilisation by segments of population

	Concentration index (CI)	Standard error
Children	0.0416***	0.0003
Adult	0.0390***	0.0002
Elderly	0.0328***	0.0002

Notes: *** indicates significance at 1%

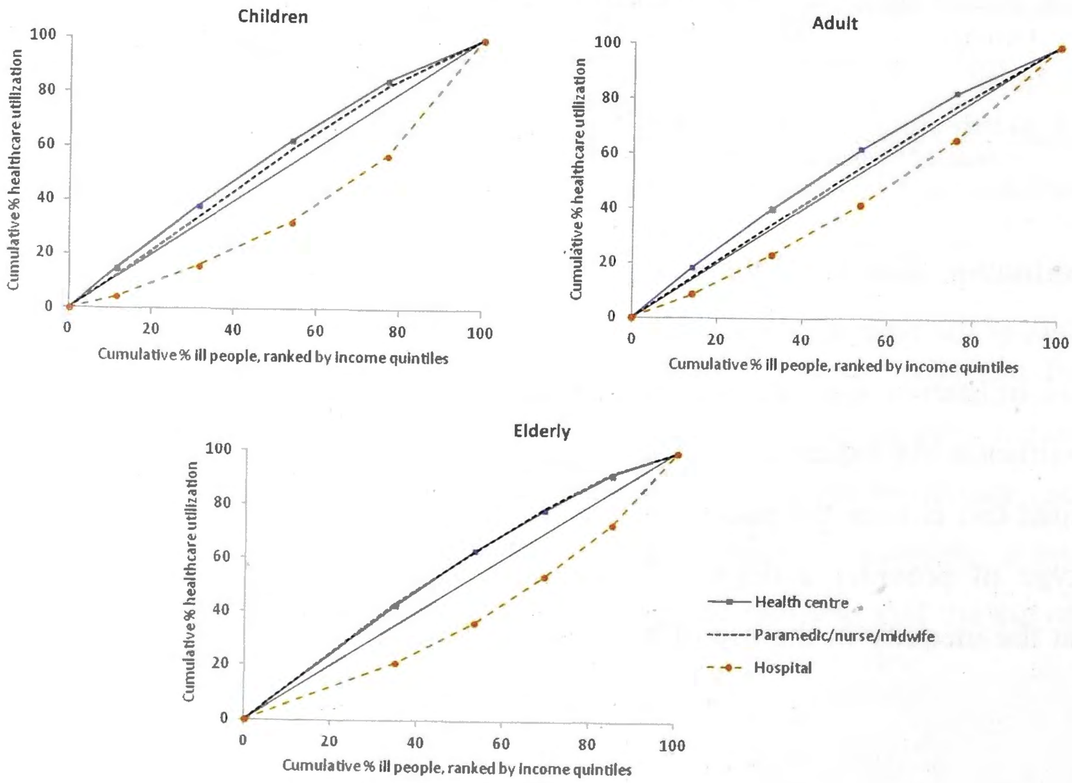
Healthcare utilisation does not differentiate between types of healthcare provider. Any visit, regardless of the type of provider, is considered as utilising healthcare. As a result, the healthcare utilisation measure may underestimate inequities in utilisation of high quality of healthcare. As indicated in Chapter 5, further differentiation between types of provider visited can change the pattern of utilisation significantly. If it is assumed that with each type of provider a degree of healthcare quality is embedded, then it is expected that the inequity in the use of high-quality healthcare providers will be more profound.

C.2. Inequity in Access to High-Quality Providers

Analysis of concentration curves by provider type reveals more variation in the inequity of healthcare utilisation (see Figure 9.2). Patients from lower income level groups are more likely to use paramedic, nurse and midwife practices and health centres, and are less likely to use hospitals, clinics and physician practices (see Chapter 5, Figure 5.10). Based on this tendency, in this analysis, type of provider is grouped into: 1) paramedic, nurse and midwife practices, 2) hospitals, clinics and physician practices, and 3) health centres (including auxiliary health centres).

The use of hospitals, clinics and physicians is concentrated among higher income groups. In other words, the poor have less access to hospitals, clinics and physician practices than do the rich. This trend is consistent for children, adults and the elderly. The area between the equality line and the hospital curve indicates the degree of concentration. The greatest income inequity on access to hospitals, clinics and physician practices is experienced by children, followed by the elderly and adults. The use of paramedic, nurse and midwife practices and health centres, in contrast, is concentrated among the poor.

Figure 9.2 Concentration curves on the effect of income levels on utilisation by provider type, among children, adults and the elderly



Quantification of concentration curves makes inequities easy to compare. Table 9.2 shows the non-standardised and standardised CI for all types of provider. The index is a quantification of the concentration curves presented in Figure 9.2. Some improvement in the CI is gained after standardising 'need' with several covariates. This index shows that the degree of inequity in access to healthcare among children and the elderly is higher than among adults, with access to hospitals, clinics and physician practices concentrated towards the rich, while access to health centres and paramedic, nurse and midwife practices is concentrated towards the poor.

Table 9.2 Concentration index of utilisation of healthcare providers

	Health Centre*		Hospital/Physician/ Clinic*		Paramedics/Nurses/ Midwives*	
	CI	Se	CI	Se	CI	Se
Non-Standardised						
Children	-0.1027	0.0002	0.2542	0.0003	-0.0635	0.0002
Adult	-0.1056	0.0001	0.1974	0.0002	-0.0892	0.0001
Elderly	-0.0690	0.0004	0.1751	0.0006	-0.1086	0.0006
Standardised						
Children	-0.1144	0.0003	0.2770	0.0003	-0.0597	0.0002
Adult	-0.1103	0.0001	0.1530	0.0002	-0.0243	0.0001
Elderly	-0.1329	0.0003	0.1838	0.0003	-0.1406	0.0003

Notes: *All concentration indexes are statistically significant at 1%

The difference in inequity in access to different healthcare providers would be meaningless or only a matter of preference if there were no systematic and embedded values attached to each type of provider to differentiate them. In fact, there are strong indications that preferences towards certain healthcare providers are related to their characteristics. Quality of service is one such characteristic.

Two indicators can be used as proxies of the quality of healthcare providers: the number of medical doctors and the quality of treatment (Donabedian, 1980). By definition, there are no medical doctors available in paramedic, nurse and midwife practices. On average, there are 1.32 medical doctors (mostly GPs) in every health centre. The number of doctors is even higher at hospitals. In 2007, on average, there were 24 medical doctors (GPs and medical specialists) in every hospital (Bahjuri-Ali et al., 2009). So far, there is no data on number of doctors in every clinic, although in practice, usually there are several doctors working in a shift system. A physician practice, as its name implies, has a physician available. Measured by the number of doctors, the quality of paramedic, nurse and midwife practices is the lowest. Hospital, clinics and physician practices are on top of the quality rank, while health centres lie in the middle.

Systematic studies on the quality of healthcare providers in Indonesia were conducted by Barber et al. (2007) and Rokx et al. (2010). Using 1997 IFLS data, Barber et al. (2007) studied variations in child and adult (including elderly) outpatient care quality, measured as scores for diagnostic and treatment ability. The study found that private physicians provide the highest quality curative care, followed by health centres. In contrast, private nurses and midwives offer below average care. A follow up study conducted by Rokx et al. (2010) using 2007 IFLS data showed an improvement in the quality of all healthcare providers. However, the relative rank of the quality among providers remains the same for both child and adult curative care. Physician practices and health centres have above average scores, while private nurses and midwives have below average scores. Hospitals (including clinics) are not included in the study.

As indicated by structural quality (number of doctors) or quality in treatment (diagnostic and treatment), paramedic, nurse and midwife practices are associated with lower quality of care as compared to health centres and hospitals, physicians and clinics. Consequently, referring to concentration curves and indexes, inequities in access to high quality healthcare are observed among all population groups, favouring populations with higher income levels. The inequity curve and index shows the use of health centres as more concentrated among the poorer population groups. Hence, health centres provide a safety net to balance out the lack of access to high-quality healthcare (hospitals, clinics and physicians) for low-income groups.

D. Policy Measures to Tackle Inequity

As suggested in Chapters 4 and 5, healthcare utilisation is associated with various demographic and non-demographic factors. After controlling for 'need' in a multivariate logistic setting, horizontal inequity can be observed in all population groups (for children, adults and the elderly). Chapter 6 provides insight into how the interaction between provider characteristics and user characteristics contributes to inequity of access to healthcare providers.

In this section, discussion on implications for policy will focus on various policy options to address income-related inequity. Intervention from the government is needed to protect against the uncertain nature of sickness, which makes it difficult for low-income groups to allocate resources for adequate healthcare (Ensor and Cooper, 2004). Under the social equity principle, measures are also needed when some groups are unable to use healthcare because of underlying unequal income distribution or unequal intra-household bargaining power (Ensor and Cooper, 2004).

Following two important findings in this study—that is, that income level is associated with healthcare utilisation and that income level is influential on the decision to choose a healthcare provider—exploration of the policy implications is directed towards increasing utilisation and access to high-quality healthcare services.

D.1. Increasing Utilisation

The inequity of healthcare utilisation for children, adults and the elderly is small but significant (shown in the concentration curves and index). The effect of income is more profound among females from lower income groups than for those from higher income groups (refer to Figure 4.9 in Chapter 4). To reduce inequity, utilisation among lower-income groups, and particular among females in lower-income groups must be increased. This can be achieved by reducing income-related barriers to provider access.

A more comprehensive and targeted approach is proposed by considering the interaction between users and provider characteristics. For example, Chapter 6 showed that on average high price deters healthcare-seekers from utilising healthcare services. However, the effect is different by place of residence and income level. Utilisation of urban dwellers and richer groups is more sensitive to price of service, but less sensitive to distance. For rural dwellers and the poor, their utilisation is more sensitive to distance, and less sensitive to price of service.

To increase overall utilisation, targeted interventions are more effective. To increase utilisation, the focus for urban areas is on the reduction of direct cost barriers such as expansion of healthcare insurance, including for the rich. For rural areas, the focus of interventions should be more on expansion of health service facilities to reduce the distance and indirect cost of service. For the poor, especially in rural areas, subsidies for transportation costs will help them in accessing health services.

To help the poor in accessing healthcare, Indonesia introduced an *ad hoc* social health scheme as a response to the economic crisis in 1998. The program has since been declared successful in preventing further healthcare utilisation decline (Pradhan et al., 2007). The program has evolved over time and a new scheme was sealed in 2005 through Askeskin – the health insurance scheme for the poor (renamed Jamkesmas in 2008).

Although Askeskin is primarily provided for poor and near-poor households, in practice, a substantial portion of the population from higher income levels also receives benefits from the program (Pradhan et al., 2007, Sparrow et al., 2010). As a result, although Askeskin is able to increase healthcare utilisation as described in Chapter 4, it does not reduce inequity effectively. According to Hidayat et al. (2004), other types of insurance (Askes insurance for civil servants and Jamsostek for workers in formal sectors) also did not reduce inequity. Therefore, it is necessary for the government to devise a scheme that is more beneficial for the poor. This could be achieved by tightening the targeting mechanism and differentiating healthcare service benefits based on income testing.

The challenge is in identifying the eligible poor for the scheme. In addition to a challenge in setting appropriate criteria of inclusion, rapid fluctuation of the poverty level across time (Suharyadi et. al., 2003) and the movement of population between the two sides of the poverty line make income testing complicated. Skoufias (2000), for example, shows a remarkable fluidity in the transition into and out of poverty, making targeting the beneficiaries of social health insurance difficult.

From the supply side, the government can also intervene to reduce the cost of service borne by users; for example, by providing subsidies for medicine and health supply costs, specifically for services that will be delivered to the urban poor. In this way, the urban poor will be assisted to catch up in terms of their utilisation, thereby reducing inequality. If the subsidy were given to all groups in urban areas, overall utilisation would be increased, without addressing equity.

Indonesia has consistently been providing subsidies for outpatient services in public health facilities, mainly in health centres. Although this can reduce the price of service in public health facilities, the impact on equity of healthcare utilisation would be more profound if the scheme were expanded to paramedic, nurse and midwife practices, which serve as the main providers for poor and rural dwellers.

The health system is inseparable from the influence of other systems, including social determinants of health and healthcare (Marmot and Wilkinson, 2006). In the broader policy context, it is important to address social economic determinants of health inequities, such as by improving income and education levels, and addressing gender inequity (since, usually, females have lower commanding power in disbursing resources). However, this measure will be complex and require a long time frame for implementation.

D.2. Increasing Quality of Services

The previous section showed that inequity in access to high-quality providers is more profound than inequity in overall healthcare utilisation. For all groups of population (children, adults and the elderly), the utilisation of high-quality providers (hospitals, private physician and clinics) is concentrated among the higher income groups. In contrast, the poor use more paramedics, nurses and midwives for outpatient services. In other words, the poor routinely access a lower quality of outpatient service than do the rich.

One of the endeavours to increase the use of high-quality health services among the poor has been to expand the number of high-quality providers such as hospitals, physicians and clinics in the community, while also reducing income-related barriers to health services access, with the expectation that low-income groups will gain better access to high-quality care. This approach has been adopted in various breakaway districts in Indonesia, primarily by constructing new hospitals with the expectation that this will increase the ability of local residents to access high-quality health services.

This approach, however, brings some adverse effects with it. For example, hospitals are more likely to be used by the rich than by the poor, and by urban dwellers since hospitals are always located in urban settings. Thus, although the hospital-building approach can increase utilisation among the poor, it has little effect on reducing overall inequity. In addition, this approach can be very costly and it is very difficult to recruit health workers due to shortages on the production side. In addition, new graduates or existing doctors are less likely to choose to work in new hospitals in breakaway districts, which are mostly located outside Java/Bali.

Another and more realistic approach is to improve the quality of current providers that are most likely to be visited by the poor; that is, paramedic, nurse and midwife practices, health centres and auxiliary health centres. Various studies have indicated that nurse practices have the largest quality deficiencies across all types of care studied: prenatal, child curative and adult curative care (Barber et al., 2007). Nurses and midwives have also reported significant training needs (Hennessy, Hick and Kawonal, 2005, Hennessy, Hick and Koesno, 2005).

Various options to improve the quality of these services include training, organisational reforms and financial incentives. In developing countries, research on quality improvement has emphasised in-service training to update knowledge and clinical ability (Barber and Gertler, 2008). The need for training should also be tailored according to need, since variation in the skill of nurses and midwives is great. For example, the quality among private midwives practicing in Java/Bali is higher than for midwives outside Java/Bali (Hennessy, 2001). Another source of variation is in the loose regulatory framework governing the quality of pre-service training, and in particular, the rapid growth of new schools without a proper credentialing process (Rokx et al., 2010).

Another approach would be affirming nurse and midwife roles, especially for village midwives, in certain clinical competencies for outpatient services. It is well known that nurses and midwives are taking on roles in clinical treatment that are beyond their job descriptions. They have to assume these roles in curative care due to the absence of a competent health workforce in certain regions. One study shows that 46% of midwives do not have a formal job description (Hennessy et al., 2005). Further, while they are taking on many responsibilities beyond their skill level, they do not have the legal support to do so (Rokx et al., 2010). As nurses and midwives are still the major healthcare providers for rural areas and lower income groups—both groups have very limited options of healthcare provider other than nurses and midwives—the government should be providing conditional privileges for them to provide outpatient services, as well as upgrading their skills.

E. Dealing with Future Healthcare Utilisation

Over the next 15 years, the size of the Indonesian population will increase by 19.6%, and utilisation of healthcare is expected to increase by 25.7%. The obvious implication of this population growth is the need for more health workers. For example, in 2006, there were about 44,564 GPs in Indonesia, or about 20 GPs per 100,000 population. The MoH standard of GP adequacy is 30 per 100,000 population. For this standard to be met by 2025, the required number of GPs will be 88,440, about double the number of GPs in 2006. The increase in the need for other health workers will vary between 51% for nurses and 187% for dentists. Table 9 presents a rough estimation of the number of health workers needed as a consequent of increased population by 2025.

Table 9.3 Existing and projected number and ratio of health workers

Health workers	2010 MoH Target (per 100,000 population)	2006		2025 (Projected)	
		Number	Per 100,000 population	Number	Deficit* (%)
General practitioners	30	44,564	20.0	88,440	98
Medical specialists	9	12,374	5.5	26,532	114
Dentists	11	11,289	5.1	32,428	187
Nurses	158	308,396	138.9	465,784	51
Midwives	75	79,152	35.4	221,100	179

Notes: *Deficit is calculated as the addition of health workers required to meet the MoH target

Data source: BPPSDMK Profile 2007 (MoH, 2007, 30).

The projection presented in Table 9.3 provides a general guideline on the number of health workers needed to provide adequate service to an increased population if the utilisation and sickness rates remain at 2006 levels. Even with a constant rate of sickness and healthcare utilisation, the projection of the need for health workers has several limitations, as it does not take into account the change in population structure, address the inequity issues, or take into account epidemiological transitions and interventions that will boost utilisation, such as universal health insurance coverage.

The structure of the population in the future is characterised by ageing. Utilisation will not grow evenly among groups of population. In 2025, utilisation is projected to increase by 89.9% among the elderly, 32.6% among adults and -9.0% (a decrease) among children. Therefore, production of each type of health worker should consider the change in target population. For example, utilisation among adults and the elderly is associated with chronic diseases. Therefore, the allocation for health workers that can deal with chronic disease-related sickness (such as medical specialists and surgeons) should be increased at a much higher rate than for health workers that do not deal with chronic diseases. For example, Adeyi et al. (2007) indicated that the need for medical doctors in East Java and Central Java due to increased chronic disease would increase 3-fold by 2030.

The decrease in the level of utilisation among children, primarily due to the decreasing number of births anticipated over the next 15 years, indicates that the number of health workers specialising in children's and maternal health (for example, paediatricians and obstetric gynaecologists) only need to be increased as a response to inequity issues rather than due to increased population.

Increasing the number of midwives and nurses as suggested in Table 9.3 would likely sustain inequity in the population, since such health workers are likely to be used by the poor and people in rural areas. In contrast, high-quality health workers such as doctors are more likely to be used by the rich and people in urban areas and by people living in Java/Bali. What is crucial is to provide more training for healthcare providers that are used by the poor and those living in rural areas, and to deploy more medical doctors into rural areas to gradually take over the roles currently being played out of necessity by underqualified paramedics, nurses and midwives in the provision of outpatient services.

Indonesia is projected to become increasingly urbanised. In 2010, about 50% of the population was living in urban areas. Urbanisation is projected to continue, and by 2025, about 60% of the population will live in urban areas (United Nations, 2011). As urban residents prefer hospitals, private physicians and clinics, the need for medical doctors is likely to rise even higher, while demand for nurses and midwives (in private practice) is likely to decline. In anticipating these changes, planning for health workforce production and distribution has to be more comprehensive, by taking into account population dynamics and issues of inequity, and replacing those health workers exiting the market.

urban residents, private hospitals, private ...
doctors is likely to ... higher, while demand ...
practices. ...
workforce production and distribution ...
account population ...
... decrease ... should consider ... the elderly ...
... health workers that can ... medical specialists and surgeons ... health workers that do not deal with ... that the need for medical ... would increase ...

... primarily due to the decreasing ... that the number of health ... (for example, paediatricians and ... as a response to inequity issues ...

... as suggested by Table ... would likely ... are likely to be used by the ... health workers such as doctors ... and by people living in ... for healthcare providers that are ... medical doctors ... in the provision of outpatient services.

... about ...% of the ... Urbanisation is projected to continue, and by ... in urban areas (United Nations, 2011). As

Chapter 10
Lessons Learned from the Study of Healthcare Utilisation

Every year a proportion of the population has some sickness symptoms. As sickness often indicates the need for healthcare service utilisation, some of these sick people seek medical care. Yet, the healthcare utilisation rate in Indonesia is quite low. According to the 2007 IFLS, only 18% of the sick population visit healthcare providers, while the majority opt to self-treat or forgo any treatment. Those who decide to seek care face a choice of healthcare provider. The pattern of choices indicates that the preference towards certain types of provider relates to the characteristics of users and of providers.

Previous studies have demonstrated associations between healthcare utilisation and choice of provider and demographic factors such as age, sex, marital status, as well as non-demographic factors such as income level, education and severity of illness. The provider's characteristics, such as price of service, travel distance to service and quality of service, have also been found as influential.

Informed by previous studies and theories of health service use, this study explored the roles of each of a set of user and provider characteristics, and further sought an understanding of the interaction of these characteristics and the corresponding effect on utilisation and choice of provider. Using information from the analysis of determinants, the effects of population growth on healthcare utilisation are then projected for the future, and the magnitude of this future use projection is compared against the effects of increased health insurance and chronic diseases.

The study employed various statistical and mathematical tools in its process. The determinant analysis employed discrete choice models including logistic, multinomial logistic and RPL regression models. Future population was projected using cohort component methods, and future healthcare utilisation was projected using propensity methods. Other tools in the analysis of healthcare utilisation inequity included the calculation of CI. Three main sets of data were used: 2007 Susenas, 2007 IFLS and 2007 Riskesdas. For population projections, the base population was taken from the 2010 Population Census data.

This study is expected to contribute to public policy by providing empirical evidence on the roles of demographic factors, social economic status and service provision in healthcare utilisation. Investigation on the inequity of access to health and the projection of future healthcare utilisation provides inputs for health system planning. For the academic research context, this study is expected to contribute to the understanding of healthcare in Indonesia, filling gaps in the research on the roles of provider characteristics and providing insights into incorporating non-demographic factors into utilisation projections.

A. Determinants of Healthcare Utilisation

This study demonstrated that healthcare utilisation in Indonesia is determined by various demographic and non-demographic factors. In general, this is in line with the behaviour framework of health service use, which describes health services as influenced by predisposing, enabling and health need factors (Andersen, 1995). Healthcare utilisation is significantly associated with age, sex and marital status. As age progresses, utilisation forms a 'sleeping-S curve', where it is high in infancy, declines during the teenage years, increases at late adulthood, and irreversibly declines among the elderly. This trajectory supports the notion that the effect of age on utilisation is not monotonic (Wolinsky, 1988).

Females' use of healthcare is generally higher than is males', except during childhood, when utilisation is the same. Females' use is also more susceptible to changes in income, employment status and household headship status, supporting the idea that female utilisation is influenced more by social stratification, gender roles and power imbalances than by biological determinants (Del Mar García-Calvente et al., 2012).

Controlling for other factors, healthcare utilisation does not vary by type of region (rural or urban), religion or ethnicity. This indicates that rurality and minority in terms of religion and ethnicity are not a source of inequity in healthcare utilisation. There is however, a difference in utilisation based on island of residence, education and income level. People living outside Java/Bali, those with a lower educational level and people from lower income brackets are less likely to use healthcare. Subscription to health insurance increases utilisation at all income levels. In effect, health insurance can increase overall utilisation, but may not decrease income-generated inequity.

Health needs are among the most influential factors in healthcare utilisation. People with poorer health or with chronic diseases use significantly more healthcare. This is consistent with the finding of previous studies (Wolinsky, 1978) and with the behaviour framework of health service use (Aday and Andersen, 1974). Continuing increases in chronic disease rate, therefore, are expected to add significant utilisation in the future.

B. Choice of Healthcare Providers

Analysis of determinants of choice of provider took a more complex approach. People seeking medical care face many options of healthcare provider. The preference towards healthcare providers is systematically determined by the healthcare seekers' demographic and non-demographic characteristics.

Females are more likely to choose health centres and paramedics, nurses and midwives, probably due to the familiarity of these facilities, which form the frontier of maternal and child health under the Indonesian health program. Males, on the other hand, prefer physician practices and hospitals. This is related to the fact that males tend to seek healthcare only when their health is deteriorating badly and the illness is severe. Physicians and hospitals are preferred in this case because they are perceived to have better skill and technology for curing more severe illness. Physicians, clinics and hospitals are preferred by older people as well. As people age, the likelihood of their experiencing chronic and senescence-related diseases increases, and thus so does their need for intensive care. Hospitals and physicians offer services that deal with this kind of illness.

Analysis of choice of providers is helping to portray the disparity in the use of certain healthcare providers. Generally, rural residents' rates of utilisation are similar to those of urban dwellers, but they use the most available providers (paramedics, nurses and midwives) and may have to sacrifice quality in favour of easy and affordable access. However, people living outside Java/Bali, and people from lower income groups, systematically have lower access to healthcare. These groups may suffer from the effects of low utilisation, as well as lack of access to high-quality services. Health insurance increases the use of healthcare, especially the use of hospitals, clinics and physician practices, among all income groups. From the policy perspective, this indicates that health insurance helps people to access healthcare, but does not necessarily reduce inequity.

The difference in association and the degree of influence of independent variables on healthcare utilisation and on choice of provider indicates that the decision to use healthcare and which healthcare provider to use is not simultaneous, but rather is a two-stage process. First, people decide whether they need to seek healthcare. Second, once having decided to seek healthcare, they choose which provider they will visit. A two-stage process in this study helps in answering some intriguing questions arising from the analysis of healthcare utilisation, such as how rural residents manage the lack of access to healthcare facilities.

C. Roles of Provider Characteristics

The demand perspective explains many variations in healthcare utilisation in Indonesia. However, many questions remain unanswered. For example, do older people choose hospitals and physicians because of their quality of care? Do people from lower economic strata choose paramedics, nurses and midwives because they are cheaper? Answering these questions required further analysis on the role of provider characteristics and their interactions with user characteristics.

Using RPL, the role of four provider characteristics (price of service, distance, number of doctors and drug availability) and their interactions with user characteristics (place of residence, income, health insurance and severity of illness) were examined. RPL is very useful for this kind of analysis. It is able to map the variations in the individual responses to provider characteristics.

The study revealed the significant roles of price of service, distance, number of doctors and drug availability on preference towards providers. However, the responses of users to provider characteristics were not uniform. There were variations in the degree of response and some of the population showed an opposite preference to the average responses. Price of service deters use of service regardless of health insurance subscription status, despite the fact that insurance should reduce the effect of price (Feldstein, 2011). This study also indicates a 'bypassing phenomenon', which occurs when patients bypass nearer healthcare providers to seek a higher-quality service.

Overall, this study benefited from the use of logistic, multinomial logistics and RPL to synthesise the determinants of healthcare use in Indonesia. It shows that the variation in healthcare utilisation and choice of provider is a result of complex interactions between user demographic, social economic, health need and provider characteristics. Acknowledging these relationships will help government in planning future policy measures.

D. Future Healthcare Utilisation

Using the medium fertility scenario, the Indonesian population is projected to increase from 245.9 million to 294.8 million during 2010–2025, representing an increase in the population of 19.6% (or 9% per annum). The highest growth of 80% is to be experienced by the elderly population. In 2025, the proportion of elderly Indonesians is projected to be double the 2010 figure. The adult population is growing at a slower rate, while the child population is tending towards a slight decrease in proportion.

Due to population growth, total healthcare utilisation is expected to increase by 25.7% between 2010 and 2025. Following the pattern of population growth, the expected increase in utilisation will be highest among the elderly (89.9%), followed by adults (89.9%). Utilisation among children is projected to decrease by 9.0%.

Demographic change is not an isolated process. It goes along with the change in non-demographic factors such as improved income, education and the chronic disease rate. The current practice of healthcare utilisation projection is based on demographic change alone, assuming that non-demographic factors remain constant at a certain level. This study demonstrated that non-demographic factors (insurance and chronic disease) also affect utilisation, both in total and in pattern of utilisation; although demographic change is still the major determinant of future utilisation.

Introducing changes in various factors associated with healthcare utilisation into the projection can provide more realistic estimates of future utilisation size and pattern. This projection method can be expanded to simulate the effects of various government interventions.

E. Policy Implications

Healthcare services in Indonesia are characterised by low utilisation and inequity of access among different social economic status groups of population. Generally, these problems are approached by providing more inputs in the supply side, such as by constructing new healthcare facilities and producing more health workers. For example, in anticipating the increased demand for healthcare due to population growth, health workforce needs are calculated by linearly multiplying by the population growth.

While this approach, due to its practicality, is common practice in most countries, effective measures in increasing utilisation require more understanding of the determinants of utilisation. Healthcare utilisation is influenced by many variables, such as demographic, social economic, health need and provider characteristics. Acknowledging the effects of these variables and their interactions enables the further refining of policy and can prevent the adverse impacts of selecting incorrect policies. The need for more health workers does not apply to all population groups. Due to the ageing population in Indonesia, the need for medical doctors that specialise in chronic and senescent-related diseases is likely to increase. In contrast, the number of paediatricians and obstetric gynaecologists only need to be increased as a response to inequity issues rather than due to increased population.

Formulating measures to tackle inequities in access to healthcare also benefits from an understanding of the effect of interactions between determinants and future population size and structure. In Indonesia, in general, income-related inequity in access to healthcare utilisation may not a big issue. However, inequity in access to high-quality providers is. Access to healthcare among children and the elderly from lower economic status groups is substantially lower. The study also found that urban dwellers are more sensitive to price of service and less sensitive to distance to healthcare providers, while rural dwellers are the opposite.

Such details on inequity and change in the population structure can guide policymakers in their future planning. For example, inequity can be addressed, among others, by providing in-service training for nurses and midwives, deploying more medical doctors to health centres and auxiliary health centres in rural and remote areas and prioritising health insurance schemes in urban areas. Without this information, policy interventions can still be sought, but they will not provide comprehensive solutions targeting the problems of low utilisation and inequity in access to quality services.

F. Academic Research Context

This study demonstrated the power of combining various methodologies in understanding the determinants of healthcare utilisation in Indonesia. It mapped the role of various demographic and non-demographic factors in influencing healthcare utilisation and choice of provider, and provided insight into the consequences of this for utilisation among the future Indonesian population. It also analysed the roles of provider characteristics, which have rarely been studied due to limitations in the synchronised household and facility-based data in less-developed countries. It employed a relatively new statistical model in dealing with provider characteristics data and investigated the interaction of provider characteristics with those of users.

Considering the scope and limitations of this study, further studies could seek to shed more light on the nature and the future of healthcare utilisation by addressing the following issues:

1. The use of cross-sectional data assumes that the different propensities to visit healthcare services by age are free from cohort effects. This has been the basis for the projection of healthcare in the future population. Determinant analysis using panel data may help in proving the change (if any) in the stability of the probability to visit by birth cohort. For Indonesia, this analysis is possible using different waves of the IFLS (1993, 1997, 2000 and 2007). Complications may arise related

to the consistency of type of variable collected in the survey, and the merging of data from the various modules and waves is painstaking. The other benefits of using panel data is in examining the effects of marital transition from single to divorced, as well as the impact of changes in health insurance subscription status.

2. The RPL model can be exploited to investigate further complex interactions among various provider and user characteristics, as well as for correlation among provider characteristics. For example, interaction between price and place of residence, and correlation between price of service and quality of service could be investigated further. Many other interesting aspects about healthcare utilisation can be explored using the RPL model.

3. This study limits itself to projecting healthcare utilisation in the future. Such a projection will likely be more dynamic if it also projects utilisation for each type of provider. This would simulate the effects of demographic changes and various policy interventions on the inequities of healthcare utilisation and better estimate future health workforce needs.

4. The projection of healthcare utilisation is deterministic. This projection would be relatively easy to carry out with several independent variables. However, if more variables are included in the projections, calculations of and the assigning of probability to visit for each possible combination of independent variables quickly increases in complexity. Stochastic projections can be used to accommodate uncertainty in probability due to unobserved variables.

References

ABDEL-AAL, R. & MANGOUD, A. 1998. Modelling and forecasting monthly patient volume at a primary health care clinic using univariate time-series analysis. *Computer Methods and Programs in Biomedicine,* 56, 235–247.

ADAY, L. A. & ANDERSEN, R. 1974. A framework for the study of access to medical care. *Health Services Research,* 9, 208.

ADB 2000. *Handbook for the economic analysis of health sector projects,* ADB Publishing.

ADEYI, O., SMITH, O. & ROBLES, S. 2007. *Public policy and the challenge of chronic non-communicable diseases,* World Bank Publications.

ADIOETOMO, S. M., KITTING, A. S. & TAUFIK, S. 1989. *Fertility transition in Indonesia: trends in proximate determinants of fertility,* Demographic Institute, Faculty of Economics, University of Indonesia, and Population Council.

AI, C., & NORTON, E. C. (2003). Interaction terms in logit and probit models. *Economics letters, 80*(1), 123-129.

AKIN, J. S., GRIFFIN, C. C., GUILKEY, D. K. & POPKIN, B. M. 1986. The demand for adult outpatient services in the Bicol region of the Philippines. *Social Science & Medicine,* 22, 321–328.

AKIN, J. S., GUILKEY, D. K. & DENTON, E. H. 1995. Quality of services and demand for health-care in Nigeria—a multinomial probit estimation. *Social Science & Medicine,* 40, 1527–1537.

AKIN, J. S. & HUTCHINSON, P. 1999. Health-care facility choice and the phenomenon of bypassing. *Health Policy and Planning,* 14, 135–151.

ALDRIDGE, J. & BECKER, S. 1993. Punishing children for caring: the hidden cost of young carers. *Children & society,* 7, 376–387.

AMOOTI-KAGUNA, B. & NUWAHA, F. 2000. Factors influencing choice of delivery sites in Rakai district of Uganda. *Social Science & Medicine,* 50, 203–213.

ANDERSEN, R. & ADAY, L. A. 1978. Access to medical care in the US: realized and potential. *Medical Care,* 533–546.

ANDERSEN, R. & NEWMAN, J. F. 2005. Societal and individual determinants of medical care utilization in the United States. *Milbank Quarterly,* 83, Online only.

ANDERSEN, R. M. 1995. Revisiting the behavioral-model and access to medical-care—does it matter. *Journal of Health and Social Behavior,* 36, 1–10.

ANDERSON, C. A. M., APPEL, L. J., OKUDA, N., BROWN, I. J., CHAN, Q., ZHAO, L., UESHIMA, H., KESTELOOT, H., MIURA, K. & CURB, J. D. 2010. Dietary sources of sodium in China, Japan, the United Kingdom, and the United States, women and men aged 40 to 59 years: the INTERMAP study. *Journal of the American Dietetic Association,* 110, 736.

ANSON, O. 1989. Marital status and women's health revisited: the importance of a proximate adult. *Journal of Marriage and the Family,* 185–194.

ARCURY, T. A., GESLER, W. M., PREISSER, J. S., SHERMAN, J., SPENCER, J. & PERIN, J. 2005.The effects of geography and spatial behavior on health care utilization among the residents of a rural region. *Health Services Research,* 40, 135–156.

ARENDT, J. N. 2012. The demand for health care by the poor under universal health care coverage. *Journal of Human Capital*, 6, 316-335.

ARON-DINE, A., EINAV, L., FINKELSTEIN, A. & CULLEN, M. R. 2012. Moral hazard in health insurance: how important is forward looking behavior? *NBER Working Paper No. 17802.* National Bureau of Economic Research.

AUDIBERT, M., HE, Y. & MATHONNAT, J. 2011. Income growth, price variation and health care demand: a mixed logit model applied to tow-period comparison in Rural China.

BAHJURI-ALI, P., HADIAT, SUBEKTI, I., TRESNA, Y. D., SULARSONO, WIKANESTRI, I. & ATMAWIKARTA, A. 2009. *Pembangunan Kesehatan dan Gizi Masyarakat 2010–2014: Arah dan Kebijakan ke Depan,* Jakarta, Bappenas.

BALDANI, M. H., MENDES, Y. B. E., DE CAMPOS LAWDER, J. A., DE LARA, A. P. I., DA SILVA RODRIGUES, M. M. A. & ANTUNES, J. L. F. 2011. Inequalities in dental services utilization among Brazilian low-income children: the role of individual determinants. *Journal of Public Health Dentistry,* 71, 46–53.

BAPPENAS 2008. *Health and nutrition development database,* Jakarta, National Development Planning Agency/State Ministry National Development Planning, Republic of Indonesia.

BAPPENAS 2010. *National medium-term development plan,* Jakarta, National Development Planning Agency/State Ministry National Development Planning, Republic of Indonesia.

BARBER, S. L. & GERTLER, P. J. 2008. Strategies that promote high quality care in Indonesia. *Health Policy,* 88, 339-347

BARBER, S. L., GERTLER, P. J. & HARIMURTI, P. 2007. Differences in access to high-quality outpatient care in Indonesia. *Health Affairs,* 26, w352–w366.

BARRETT, R., KUZAWA, C. W., MCDADE, T. & ARMELAGOS, G. J. 1998. Emerging and re-emerging infectious diseases: the third epidemiologic transition. *Annual Review of Anthropology,* 247–271.

BELAND, F. 1988. Utilization of health services as events: an exploratory study. *Health Services Research,* 23, 295.

BELL, R. A. & KRAVITZ, R. L. 2008. Physician counselling for hypertension: what do doctors really do? *Patient Education and Counselling,* 72, 115.

BELLON SAAMENO, J. A., DELGADO SANCHEZ, A., LUNA DEL CASTILLO, J. D. & LARDELLI CLARET, P. 1995. Influence of age and sex on various types of utilization of the primary health care. *Gaceta sanitaria/S.E.S.P.A.S,* 9, 343–53.

BERMAN, P., ORMOND, B. A. & GANI, A. 1987. Treatment use and expenditure on curative care in rural Indonesia. *Health Policy and Planning,* 2, 289–300.

BERMAN, P. 1989. Cost efficiency in primary health care: studies of health facilities in Indonesia. Health Policy and Planning, 4, 316-322.

BERRA, S., BORRELL, C., RAJMIL, L., ESTRADA, M. D., RODRÍGUEZ, M., RILEY, A. W., FORREST, C. B. & STARFIELD, B. 2006. Perceived health status and use of healthcare services among children and adolescents. *The European Journal of Public Health,* 16, 405–414.

BERRA, S., TEBÉ, C., ERHART, M., RAVENS-SIEBERER, U., AUQUIER, P., DETMAR, S., HERDMAN, M., ALONSO, J. & RAJMIL, L. 2009. Correlates of use of health care services by children and adolescents from 11 European countries. *Medical Care,* 47, 161.

BERTAKIS, K. D., AZARI, R., HELMS, L. J., CALLAHAN, E. J. & ROBBINS, J. A. 2000. Gender differences in the utilization of health care services. *Journal of Family Practice,* 49, 147–152.

BHUTTA, Z. A. & AZRA HAIDER, B. 2008. Effect of maternal multiple micronutrient supplementation on fetal loss and infant death in Indonesia: a double-blind cluster-randomised trial. Commentary. *Lancet,* 371.

BIRCH, S., LAVIS, J., MARKHAM, B., WOODWARD, C. & O'BRIAN-PALLAS, L. 1994. *Nursing requirements for Ontario over the next twenty years: development and application of estimation methods,* Centre for Health Economics and Policy Analysis, McMaster University.

BLOOM, S., WYPIJ, D. & GUPTA, M. 2001. Dimensions of women's autonomy and the influence on maternal health care utilization in a North Indian city. *Demography,* 38, 67–78.

BONGAARTS, J. & POTTER, R. G. 1983. *Fertility, biology, and behavior: an analysis of the proximate determinants,* Academic Press New York.

BOOTH, H. 1984. Transforming Gompertz's function for fertility analysis: the development of a standard for the relational Gompertz function. *Population Studies,* 38, 495–506.

BOOTH, H. 2006. Demographic forecasting: 1980 to 2005 in review. *International Journal of Forecasting,* 22, 547–581.

BORAH, B. J. 2006. A mixed logit model of health care provider choice: analysis of NSS data for rural India. *Health Economics,* 15, 915–932.

BOURNE, P. A. 2009. Socio-demographic determinants of health care-seeking behaviour, self-reported illness and self-evaluated health status in Jamaica. *International Journal of Collaborative Research on Internal Medicine & Public Health,* 1, 101–130.

BOX, G. E. P. & TIDWELL, P. W. 1962.Transformation of the independent variables. *Technometrics,* 531–550.

BPS, BAPPENAS & UNFPA 2008. Indonesia population projection 2005–2025.

BPS & MACRO INTERNATIONAL 2008. *Indonesia demographic and health survey 2007,* Calverton, Maryland, USA, BPS and Macro International.

BRASS, W. 1971. On the scale of mortality. *Biological aspects of demography,* 69–110.

BRASS, W. 1981. The use of the Gompertz relational model to estimate fertility. International Population Conference, Manila, 1981. IUSSP Liège, 345–362.

BRAVEMAN, P. 2006. Health disparities and health equity: concepts and measurement. *Annual Review of Public Health,* 27, 167–194.

BUCHMUELLER, T. C., GRUMBACH, K., KRONICK, R. & KAHN, J. G. 2005. Book review: the effect of health insurance on medical care utilization and implications for insurance expansion: a review of the literature. *Medical Care Research and Review,* 62, 3–30.

BUDI, H. 2008. Are there differences between unconditional and conditional demand estimates? Implications for future research and policy. *Cost Effectiveness and Resource Allocation,* 6.

BURNER, S. T., WALDO, D. R. & MCKUSICK, D. R. 1992. National health expenditures projections through 2030. *Health Care Financing Review,* 14, 1.

BUSKE, L. 2007. Projections of physician supply in Canada. *Health Human Resources, Connecting Issues and People.*

BYRNE, D., GOEREE, M. S., HIEDEMANN, B. & STERN, S. 2009. Formal home health care, informal care and family decision making. *International Economic Review,* 50, 1205–1242.

CAFFERATA, G. L. & KASPER, J. D. 1985. Family structure and children's use of ambulatory physician services. *Medical Care,* 23, 350–360.

CALDWELL, J. C. 1980. *The wealth flows theory of fertility decline,* International Union for the Scientific Study of Population.
CALDWELL, J. C. 2005. On net intergenerational wealth flows: an update. *Population and Development Review,* 31, 721–740.
CAMERON, A. C., TRIVEDI, P. K., MILNE, F. & PIGGOTT, J. 1988. A micro econometric model of the demand for health care and health insurance in Australia. *The Review of Economic Studies,* 55, 85–106.
CAMPBELL, N., ELLIOTT, A., SHARP, L., RITCHIE, L., CASSIDY, J. & LITTLE, J. 2000. Rural factors and survival from cancer: analysis of Scottish cancer registrations. *British Journal of Cancer,* 82, 1863–1866.
CANAVIRI, J. 2007. A random parameter logit model for modelling health care provider choice in Bolivia. *Oklahoma State University, MPRA Paper.*
CARD, D., DOBKIN, C. & MAESTAS, N. 2004. *The impact of nearly universal insurance coverage on health care utilization and health: evidence from Medicare.* National Bureau of Economic Research.
CARLSEN, F. & GRYTTEN, J. 2000. Consumer satisfaction and supplier induced demand. *Journal of Health Economics,* 19, 731–753.
CARPENTER, E. S. 1980. Children's health care and the changing role of women. *Medical Care,* 1208–1218.
CASSEDY, A., FAIRBROTHER, G. & NEWACHECK, P. W. 2008. The impact of insurance instability on children's access, utilization, and satisfaction with health care. *Ambulatory Pediatrics,* 8, 321–328.
CHAMBERS, E. A. & COX, D. R. 1967. Discrimination between alternative binary response models. *Biometrika,* 54, 573–578.
CHANG, J. B. & LUSK, J. L. 2010. Mixed logit models: accuracy and software choice. *Journal of Applied Econometrics,* 26, 167–172.
CHASSIN, M. R. & GALVIN, R. W. 1998. The urgent need to improve health care quality. *JAMA,* 280, 1000–1005.
CHAUDHURY, N., HAMMER, J., KREMER, M., MURALIDHARAN, K. & ROGERS, F. H. 2006. Missing in action: teacher and health worker absence in developing countries. *The Journal of Economic Perspectives,* 20, 91–116.
CHENG, S. H. & CHIANG, T. L. 1997. The effect of universal health insurance on health care utilization in Taiwan. *JAMA,* 278, 89–93.
CHENG, T.-M. 2003. Taiwan's new national health insurance program: genesis and experience so far. *Health Affairs,* 22, 61–76.
CHERNICHOVSKY, D. & MEESOOK, O. A. 1986. Utilization of health services in Indonesia. *Social Science & Medicine,* 23, 611–620.
CLEARY, P. D., MECHANIC, D. & GREENLEY, J. R. 1982. Sex differences in medical care utilization: an empirical investigation. *Journal of Health and Social Behavior,* 106–119.
COALE, A. J. 1969. The decline of fertility in Europe from the French Revolution to World War II. *Fertility and Family Planning: A World View,* 3–24.
COALE, A. J. & TRUSSELL, T. J. 1974. Model fertility schedules: variations in the age structure of childbearing in human populations. *Population Index,* 185–258.
CONGDON, P. 1980. Forecasting births in Greater London: an application of the Easterlin hypothesis. *Population Studies,* 34, 267–278.
CONGDON, P. 1989. Fertility forecasts and structural interpretations: an application to London and England and Wales. *Espace, Populations, Sociétés,* 7, 177–188.
COORY, M. D. 2004. Ageing and healthcare costs in Australia: a case of policy-based evidence? *Medical Journal of Australia,* 180, 581–584.

CROMWELL, J., ROSENBACH, M. L., POPE, G. C., BUTRICA, B. & PITCHER, J. D. 1991. CRNA manpower forecasts: 1990–2010. *Medical Care,* 628–644.

CULYER, A. J. & WAGSTAFF, A. 1993. Equity and equality in health and health care. *Journal of Health Economics,* 12, 431–457.

CUTLER, D. M. & SHEINER, L. 1998. *Demographics and medical care spending: standard and non-standard effects.* National Bureau of Economic Research.

DA LA HOZ, K. F. & LEON, D. A. 1996. Self-perceived health status and inequalities in use of health services in Spain. *International Journal of Epidemiology,* 25, 593–603.

DANAEI, G., FINUCANE, M. M., LIN, J. K., SINGH, G. M., PACIOREK, C. J., COWAN, M. J., FARZADFAR, F., STEVENS, G. A., LIM, S. S. & RILEY, L. M. 2011. National, regional, and global trends in systolic blood pressure since 1980: systematic analysis of health examination surveys and epidemiological studies with 786 country-years and 5.4 million participants. *The Lancet,* 377, 568–577.

DAS, J., HAMMER, J. & LEONARD, K. 2008. The quality of medical advice in low-income countries. *The Journal of Economic Perspectives,* 22, 93-114.

DAVANZO, J. E. 1994. *The relationship between autonomy and Medicare utilization in an elderly sample.* UCLA.

DEL MAR GARCÍA-CALVENTE, M., HIDALGO-RUZZANTE, N., DEL RÍO-LOZANO, M., MARCOS-MARCOS, J., MARTÍNEZ-MORANTE, E., MAROTO-NAVARRO, G., MATEO-RODRÍGUEZ, I. & GIL-GARCÍA, E. 2012. Exhausted women, tough men: a qualitative study on gender differences in health, vulnerability and coping with illness in Spain. *Sociology of Health & Illness,* 34, 911-926.

DEPARTMENT OF LAW AND HUMAN RIGHTS 2011. *Report on the number of passports issued by Directorate General of Immigration.* Available: http://www.imigrasi.go.id [Accessed November 2011].

DIEHR, P. 1999. Methods for analysing health care utilization and costs. *Annual Review of Public Health,* 20, 125–144.

DONABEDIAN, A. 1966. Evaluating the quality of medical care. *The Milbank Memorial Fund Quarterly,* 44, 166–206.

DONABEDIAN, A. 1978. The quality of medical care. *Science,* 200, 856.

DONABEDIAN, A. 1980. Methods for deriving criteria for assessing the quality of medical care. *Medical Care Review,* 37, 653.

DONABEDIAN, A. 2005. Evaluating the quality of medical care. *Milbank Quarterly,* 83, 691–729.

DONG, H., GBANGOU, A., DE ALLEGRI, M., POKHREL, S. & SAUERBORN, R. 2008. The differences in characteristics between health-care users and non-users: implication for introducing community-based health insurance in Burkina Faso. *The European Journal of Health Economics,* 9, 41–50.

DOORSLAER, E. K. A., WAGSTAFF, A. & BLEICHRODT, H. 1997. Income-related inequalities in health: some international comparisons. *Journal of Health Economics,* 16, 93–112.

DOR, A., GERTLER, P. & VAN DER GAAG, J. 1987. Non-price rationing and the choice of medical care providers in rural Cote d'Ivoire. *Journal of Health Economics,* 6, 291–304.

DORMONT, B., GRIGNON, M. & HUBER, H. 2006. Health expenditure growth: reassessing the threat of ageing. *Health Economics,* 15, 947–963.

DOW, W. 1995. Unconditional demand for curative health inputs: does selection on health status matter in the long run. *RAND Labor and Population Program Working Paper Series,* 95, 22.

DZATOR, J. & ASAFU-ADJAYE, J. 2004. A study of malaria care provider choice in Ghana. *Health Policy,* 69, 389–401.

EDMONSTON, B. & MICHALOWSKI, M. 2004. International migration. *In:* SWANSON, D., SIEGEL, J. S. & SHRYOCK, H. S. (eds.), *The methods and materials of demography.* Emerald Group Publishing.

ELLIOTT, P., STAMLER, J., NICHOLS, R., DYER, A. R., STAMLER, R., KESTELOOT, H. & MARMOT, M. 1996. Intersalt revisited: further analyses of 24 hour sodium excretion and blood pressure within and across populations. *BMJ,* 312, 1249–1253.

ENSOR, T. & COOPER, S. 2004. Overcoming barriers to health service access: influencing the demand side. *Health Policy and Planning,* 19, 69–79.

ENTERLINE, P. E., MCDONALD, J. C., MCDONALD, A. D., DAVIGNON, L. & SALTER, V. 1973. Effects of free medical care on medical practice—the Quebec experience. *New England Journal of Medicine,* 288, 1152–1155.

ENTERLINE, P. E., SALTER, V., MCDONALD, A. D. & MCDONALD, J. C. 1973. The distribution of medical services before and after free medical care—the Quebec experience. *New England Journal of Medicine,* 289, 1174–1178.

ERLYANA, E., DAMRONGPLASIT, K. K. & MELNICK, G. 2011. Expanding health insurance to increase health care utilization: will it have different effects in rural vs. urban areas? *Health Policy,* 100, 273–281.

EVANS, R. G., MCGRAIL, K. M., MORGAN, S. G., BARER, M. L. & HERTZMAN, C. 2001. APOCALYPSE NO: Population aging and the future of health care systems. *Canadian Journal on Aging/Revue canadienne du vieillissement,* 20, 160–191.

EVANS, R. G. & WILLIAMSON, M. F. 1978. *Extending Canadian health insurance: options for pharmacare and denticare,* Ontario Economic Council.

FAN, L., SHAH, M. N., VEAZIE, P. J. & FRIEDMAN, B. 2011. Factors associated with emergency department use among the rural elderly. *The Journal of Rural Health,* 27, 39–49.

FAWCUS, S., MBIZVO, M., LINDMARK, G. & NYSTROM, L. 1996. A community-based investigation of avoidable factors for maternal mortality in Zimbabwe. *Studies in Family Planning,* 27, 319–327.

FELDSTEIN, P. J. 1966. Research on the demand for health services. *The Milbank Memorial Fund Quarterly,* 44, 128–165.

FELDSTEIN, P. J. 1996. *Health care economics,* New York, Wiley.

FELDSTEIN, P. J. 2011. *Health care economics,* Delmar Pub.

FOLLAND, S., GOODMAN, A. C. & STANO, M. 2012. *Economics of health and health care, the international version (7e),* Pearson Higher Ed., USA.

FOREMAN, S. E., YU, L. C., BARLEY, D. & CHEN, L.-W. 1998. Use of health services by Chinese elderly in Beijing. *Medical Care,* 36, 1265–1282.

FORREST, C. B. 2004. Outcomes research on children, adolescents, and their families: directions for future inquiry. *Medical Care,* 42, III-19–III-23.

FOSSE, N. E. & HAAS, S. A. 2009. Validity and stability of self-reported health among adolescents in a longitudinal, nationally representative survey. *Pediatrics,* 123, e496–e501.

FUCHS, V. R. 1984. *'Though much is taken'—reflections on aging, health, and medical care.* National Bureau of Economic Research Cambridge, Mass., USA.

FUSS, M. & MCFADDEN, D. 1978. Production economics: a dual approach to theory and applications. North-Hollad Publishing Company

GEORGE, M., SMITH, S., SWANSON, D. & TAYMAN, J. 2004. Population projections. *In:* SIEGEL, J. S. & SWANSON, D. (eds.), *The methods and materials of demography.* 2nd ed.: Elseiver Academic Press.

GERTLER, P. & GAAG, J. 1990. *The willingness to pay for medical care: evidence from two developing countries,* Johns Hopkins University Press.

GERTLER, P., LOCAY, L. & SANDERSON, W. 1987. Are user fees regressive?: The welfare implications of health care financing proposals in Peru. *Journal of Econometrics,* 36, 67–88.

GERTLER, P. J. & MOLYNEAUX, J. W. 1994. How economic development and family planning programs combined to reduce Indonesian fertility. *Demography,* 31, 33–63.

GETZEN, T. E. 2004. *Health economics: fundamentals and flow of funds,* Wiley.

GIBBS, A., PEARSE, E. J., SHEEHAN, J. A., MELEADY, K. T., JAYASINHA, H. & JONES, N. 2008. Estimating and projecting subacute care demand: findings from a review of international methods. *Australian Health Review,* 32, 778–785.

GILBERT, G. H., BRANCH, L. G. & LONGMATE, J. 1993. Dental care use by US veterans eligible for VA care. *Social Science & Medicine,* 36, 361–370.

GILL, J. 2001. *Generalized linear models: a unified approach,* Sage Publications, Inc.

GISH, O., MALIK, R. & SUDHARTO, P. 1988. Who gets what? Utilization of health services in Indonesia. *The International Journal of Health Planning and Management,* 3, 185–196.

GLANZ, K., RIMER, B. K. & VISWANATH, K. 2008. *Health behavior and health education: theory, research, and practice,* Jossey-Bass Inc. Pub.

GOTSADZE, G., BENNETT, S., RANSON, K. & GZIRISHVILI, D. 2005. Health care-seeking behaviour and out-of-pocket payments in Tbilisi, Georgia. *Health Policy and Planning,* 20, 232–242.

GREENE, W. 2010. Testing hypotheses about interaction terms in nonlinear models. *Economics Letters*, 107(2), 291-296.

GREENE, W. H. & ZHANG, C. 2003. *Econometric analysis,* Prentice Hall, Upper Saddle River, NJ.

GROBLER, C. & STUART, I. C. 2007. Health care provider choice. *South African Journal of Economics,* 75, 327–350.

ROSSMAN, M. 1972. On the Concept of Health Capital and the Demand for Health. Journal of Political Economy, 80, 223-255.

GRUBER, J. & WISE, D. 2001. *An international perspective on policies for an aging society.* National Bureau of Economic Research.

GUENDELMAN, S. 1991. Health Care Users Residing on the Mexican Border What Factors Determine Choice of the U.S. or Mexican Health System? Medical Care, 29, 419-429.

GUPTA, I., DASGUPTA, P. & GROWTH, I. O. E. 2000. *Demand for curative health care in rural India: choosing between private, public, and no care,* Institute of Economic Growth.

GWATKIN, D. R., RUSTEIN, S., JOHNSON, K., PANDE, R. & WAGSTAFF, A. 2003. *Initial country-level information about socio-economic differentials in health, nutrition and population, vols. I and II.* Washington, DC: World Bank. Health, Population, and Nutrition Division.

HABTOM, G. K. & RUYS, P. 2007. The choice of a health care provider in Eritrea. *Health Policy,* 80, 202–217.

HADLEY, J. 2003. Sicker and poorer—the consequences of being uninsured: a review of the research on the relationship between health insurance, medical care use, health, work, and income. *Medical Care Research and Review,* 60, 3S–75S.
HAHN, E. D. & SOYER, R. 2005. Probit and logit models: differences in the multivariate realm. *Working paper,* http://home.gwu.edu/~soyer/mv1h.pdf
HALIM, N., BOHARA, A. K. & RUAN, X. 2011. Healthy mothers, healthy children: does maternal demand for antenatal care matter for child health in Nepal? *Health Policy and Planning,* 26, 242–256.
HALL, T. L., REINKE, W. A. & LAWRENCE, D. 1975. Measurement and projection of the demand for health care: the Chilean experience. *Medical Care,* 511–522.
HALLDÓRSSON, M., KUNST, A. E., KÖHLER, L. & MACKENBACH, J. P. 2002. Socioeconomic differences in children's use of physician services in the Nordic countries. *Journal of Epidemiology and Community Health,* 56, 200–204.
HAUG, M. R. 1981. Age and medical care utilization patterns. *Journal of Gerontology,* 36, 103–111.
HAWKINS, L. 2009. Pharmaceutical: Why reform is needed. World Bank
HAYNES, R., BENTHAM, C., LOVETT, A. & GALE, S. 1999. Effects of distances to hospital and GP surgery on hospital inpatient episodes, controlling for needs and provision. *Social Science & Medicine,* 49, 425 - 433
HAWAII HEALTH INFORMATION CORPORATION 2004. Maui beds needs study 2005–2025. Final Report. http://hawaii.gov/shpda/resources-publications/shmauibe.pdf
HEINZELMANN, F. 1962. Factors in prophylaxis behavior in treating rheumatic-fever—an exploratory study. *Journal of Health and Human Behavior,* 3, 73–81.
HEISE, D. R. 1969. Problems in path analysis and causal inference. *Sociological Methodology,* 1, 38–73.
HELIGMAN, L. & POLLARD, J. H. 1980. The age pattern of mortality. *Journal of the Institute of Actuaries,* 49–80.
HELLER, P. S. 1982. A model of the demand for medical and health services in Peninsular Malaysia. *Social Science & Medicine,* 16, 267–284.
HENNESSY, D. 2001. *Assessment of role, job function and performance of nurse and midwives in community and hospital settings.* World Health Organization Regional Office for South-East Asia, New Delhi.
HENNESSY, D., HICKS, C. & KOESNO, H. 2005. The training and development needs of midwives in Indonesia. *Human Resources for Health.*
HENNESSY, D., HICKS, C. & KAWONAL, Y. 2005. A methodology for assessing the professional development needs of nurses and midwives in Indonesia: Part 1. *Human Resources for Health.*
HENRIPIN, J. 1994. The financial consequences of population aging. *Canadian Public Policy/Analyse de Politiques,* 78–94.
HENSHER, D. A. & GREENE, W. H. 2003. The mixed logit model: the state of practice. *Transportation,* 30, 133–176.
HIBBARD, J. H. & POPE, C. R. 1983. Gender roles, illness orientation and use of medical services. *Social Science & Medicine,* 17, 129–137.
HIDAYAT, B. 2008. Are there differences between unconditional and conditional demand estimates? Implications for future research and policy. *Cost Effectiveness and Resource Allocation,* 6, 15.
HIDAYAT, B. & POKHREL, S. 2009. The selection of an appropriate count data model for modelling health insurance and health care demand: case of Indonesia. *International Journal of Environmental Research and Public Health,* 7, 9–27.

HIDAYAT, B., THABRANY, H., DONG, H. & SAUERBORN, R. 2004. The effects of mandatory health insurance on equity in access to outpatient care in Indonesia. *Health Policy and Planning,* 19, 322–335.
HOCHBAUM, G. M. 1958. *Public participation in medical screening programs: a socio-psychological study,* US Department of Health, Education, and Welfare, Public Health Service, Bureau of State Services, Division of Special Health Services, Tuberculosis Program.
HOEM, J. M., MADIEN, D., NIELSEN, J. L., OHLSEN, E. M., HANSEN, H. O. & RENNERMALM, B. 1981. Experiments in modelling recent Danish fertility curves. *Demography,* 18, 231–244.
HOLL, J. L., SZILAGYI, P. G., RODEWALD, L. E., SHONE, L. P., ZWANZIGER, J., MUKAMEL, D. B., TRAFTON, S., DICK, A. W., BARTH, R. & RAUBERTAS, R. F. 2000. Evaluation of New York State's Child Health Plus: access, utilization, quality of health care, and health status. *Pediatrics,* 105, 711–718.
HOLLY, A., GARDIOL, L., DOMENIGHETTI, G. & BRIGITTE, B. 1998. An econometric model of health care utilization and health insurance in Switzerland. *European Economic Review,* 42, 513-522.
HOROWITZ, A. 1985. Sons and daughters as caregivers to older parents: differences in role performance and consequences. *The Gerontologist,* 25, 612–617.
HORWITZ, S. M. C., MORGENSTERN, H. & BERKMAN, L. F. 1985. The impact of social stressors and social networks on pediatric medical care use. *Medical Care,* 946–959.
HOSMER, D. W., LEMESHOW, S. & KLAR, J. 1988. Goodness-of-Fit Testing for the Logistic Regression Model when the Estimated Probabilities are Small. Biometrical Journal, 30, 911-924.
HUGHES, M. & GOVE, W. R. 1981. Living Alone, Social Integration, and Mental Health. American Journal of Sociology, 87,48-74.
HUGO, G. J., HULL, T. H., JONES, G. W. & HULL, V. J. 1987. *The demographic dimension in Indonesian development,* Oxford University Press, Singapore.
HULKA, B.S. & WHEAT, J R. 1985. Patterns of Utilization: The Patient Perspective. Medical Care, 23, 438-460.
HULL, T. H. 1987. Fertility decline in Indonesia: an institutionalist interpretation. *International Family Planning Perspectives,* 90–95.
HULL, T. H. 2010. Estimates of Indonesian population numbers: first impressions from the 2010 census. *Bulletin of Indonesian Economic Studies,* 46, 371–375.
HULL, T. H. & HARTANTO, W. 2009. Resolving contradictions in Indonesian fertility estimates. *Bulletin of Indonesian Economic Studies,* 45, 61–71.
ISKANDAR, N. 1970. *Some monographic studies on the population in Indonesia,* Lembaga Demografi, Universitas Indonesia.
ISSERMAN, A. M. 1984. Projection, forecast, and plan on the future of population forecasting. *Journal of the American Planning Association,* 50, 208–221.
JACOBS, B., IR, P., BIGDELI, M., ANNEAR, P. L. & VAN DAMME, W. 2012. Addressing access barriers to health services: an analytical framework for selecting appropriate interventions in low-income Asian countries. *Health Policy and Planning,* 27, 288-300.
JANICKE, D. M., FINNEY, J. W. & RILEY, A. W. 2001. Children's health care use: a prospective investigation of factors related to care-seeking. *Medical Care,* 39, 990.
JATRANA, S. & CRAMPTON, P. 2010. Gender differences in general practice utilisation in New Zealand. *Journal of Primary Health Care,* 1, 261–269.

JOHNSTON, G. A. & TEASDALE, A. 1999. *Population ageing and health spending: 50-year projections*, Ministry of Health.

JONES, A. P., BENTHAM, G., HARRISON, B. D. W., JARVIS, D., BADMINTON, R. M. & WAREHAM, N. J. 1998. Accessibility and health service utilization for asthma in Norfolk, England. *Journal of Public Health,* 20, 312–317.

JORDAN, H., RODERICK, P., MARTIN, D. & BARNETT, S. 2004. Distance, rurality and the need for care: access to health services in South West England. *International Journal of Health Geographics,* 3, 21.

KAKWANI, N., WAGSTAFF, A. & VAN DOORSLAER, E. 1997. Socioeconomic inequalities in health: measurement, computation, and statistical inference. *Journal of Econometrics,* 77, 87–103.

KAO, E. P. C. & TUNG, G. G. 1980. Forecasting demands for inpatient services in a large public health care delivery system. *Socio-Economic Planning Sciences,* 14, 97–106.

KARANCA-MANDIC, P., NORTON, E. C., & DOWD, B. 2012. Interaction terms in nonlinear models. *Health services research, 47*(1pt1), 255-274.

KEGELES, S. S., KIRSCHT, J. P., HAEFNER, D. P. & ROSENSTOCK, I. M. 1965. Survey of beliefs about cancer-detection and taking Papanicolaou tests. *Public Health Reports,* 80, 815–823.

KELLEHER, K. & STARFIELD, B. 1990. Health care use by children receiving mental health services. *Pediatrics,* 85, 114–118.

KELLEY, E., MOY, E., STRYER, D., BURSTIN, H. & CLANCY, C. 2005. The national healthcare quality and disparities reports: an overview. *Medical Care,* 43, I.

KEYFITZ, N. 1965. Indonesian population and the European industrial revolution. *Asian Survey,* 503–514.

KEYFITZ, N. 1993. Fertility: the major component of future population. *In:* BOGUE, D., ARRIAGA, E. & ANDERTON, D. (eds.), *Readings in population research methodology.* Social Development Center.

KHAN, M., WALLEY, J., WITTER, S., IMRAN, A. & SAFDAR, N. 2002. Costs and cost-effectiveness of different DOT strategies for the treatment of tuberculosis in Pakistan. *Health Policy and Planning,* 17, 178–186.

KIRK, D. 1996. Demographic transition theory. *Population Studies,* 50, 361–387.

KLEMICK, H., LEONARD, K. L. & MASATU, M. C. 2009. Defining access to health care: evidence on the importance of quality and distance in rural Tanzania. *American Journal of Agricultural Economics,* 91, 347–358.

KNUDSEN, C., MCNOWN, R. & ROGERS, A. 1993. Forecasting fertility: an application of time series methods to parameterized model schedules. *Social Science Research,* 22, 1–23.

KONG, M.-K. & LEE, H.-K. 1999. Demand for medical care, consumption and cointegration. *Economics Letters,* 62, 325-330.

KRUK, M. E., MBARUKU, G., MCCORD, C. W., MORAN, M., ROCKERS, P. C. & GALEA, S. 2009. Bypassing primary care facilities for childbirth: a population-based study in rural Tanzania. *Health Policy and Planning,* 24, 279–288.

KRUSE, I., PRADHAN, M. & SPARROW, R. 2011. Marginal benefit incidence of public health spending: evidence from Indonesian sub-national data. *Journal of Health Economics.* , 31, 147-157.

KWON, S. 2009. Thirty years of national health insurance in South Korea: lessons for achieving universal health care coverage. *Health Policy and Planning,* 24, 63–71.

LANCE, P. M. 2003. *The demand for health care in lower income nations: theory, econometrics and empirical evidence from Indonesia.* Ph.D. diss., University of North Carolina at Chapel Hill.

LANDRY, A. 1987. Adolphe Landry on the demographic revolution. *Population and Development Review,* 13, 731–740.

LAWSON, D. 2004. *Determinants of health seeking behaviour in Uganda: is it just income and user fees that are important?* University of Manchester.

LEE, L., ROSENZWEIG, M. R. & PITT, M. M. 1997. The effects of improved nutrition, sanitation, and water quality on child health in high-mortality populations. *Journal of Econometrics,* 77, 209–235.

LEE, R. & MILLER, T. 2002. An approach to forecasting health expenditures, with application to the US Medicare system. *Health Services Research,* 37, 1365–1386.

LEE, R. D. 1993. Modelling and forecasting the time series of US fertility: age distribution, range, and ultimate level. *International Journal of Forecasting,* 9, 187–202.

LEONARD, K. L., MLIGA, G. R. & MARIAM, D. H. 2002. Bypassing health centres in Tanzania: revealed preferences for quality. *Journal of African Economies,* 11, 441–471.

LEPINE, A. & LE NESTOUR, A. 2011. Health care utilization in rural Senegal: the facts prior to the extension of health insurance to farmers. *Working paper series.* http://ssrn.com/abstract=1965752

LESTHAEGHE, R. & SURKYN, J. 1988. Cultural dynamics and economic theories of fertility change. *Population and Development Review,* 14, 1–45.

LEVENTHAL, H., HOCHBAUM, G. & ROSENSTOCK, I. 1960. The impact of Asian influenza on community life: a study in five cities. *US Public Health Service Publication.*

LIEBERMAN, S. S. & MARZOEKI, P. 2002. Health strategy in a post-crisis, decentralizing Indonesia. *Health, Nutrition, and Population Discussion Paper.*

LITVACK, J. I. & BODART, C. 1993. User fees plus quality equals improved access to health care: results of a field experiment in Cameroon. *Social Science & Medicine,* 37, 369–383.

LÓPEZ-CEVALLOS, D. F. & CHI, C. 2010. Health care utilization in Ecuador: a multilevel analysis of socio-economic determinants and inequality issues. *Health Policy and Planning,* 25, 209–218.

LOVELL, C., RODRÍGUEZ-ÁLVAREZ, A. & WALL, A. 2009. The effects of stochastic demand and expense preference behaviour on public hospital costs and excess capacity. *Health Economics,* 18, 227–235.

LOVETT, A., HAYNES, R., SUNNENBERG, G. & GALE, S. 2002. Car travel time and accessibility by bus to general practitioner services: a study using patient registers and GIS. *Social Science & Medicine,* 55, 97–111.

LU, J.-F. R. & HSIAO, W. C. 2003. Does universal health insurance make health care unaffordable? Lessons from Taiwan. *Health Affairs,* 22, 77–88.

LUTZ, W., SANDERSON, W. C. & SCHERBOV, S. 1998. Expert-based probabilistic population projections. *Population and Development Review,* 24, 139–155.

LUTZ, W., SANDERSON, W. & SCHERBOV, S. 2001. *The end of world population growth,* International Institute for Applied Systems Analysis.

MACINTYRE, S., HUNT, K. & SWEETING, H. 1996. Gender differences in health: are things really as simple as they seem? *Social Science & Medicine,* 42, 617–624.

MANGALORE, R., KNAPP, M. & JENKINS, R. 2007. Income-related inequality in mental health in Britain: the concentration index approach. *Psychological medicine,* 37, 1037–1046.

MANNING JR, W. G., NEWHOUSE, J. P. & WARE JR, J. E. 1982. The status of health in demand estimation; or, beyond excellent, good, fair, poor. In: FUCHS, V. (ed.) *Economic Aspects of Health.* University of Chicago Press. http://www.nber.org/chapters/c6548.pdf

.

MANNING, W. G., NEWHOUSE, J. P., DUAN, N., KEELER, E. B. & LEIBOWITZ, A. 1987. Health insurance and the demand for medical care: evidence from a randomized experiment. *The American Economic Review,* 77, 251–277.

MARMOT, M. G. & WILKINSON, R. G. 2006. *Social determinants of health,* Oxford University Press, USA.

MCDONALD, J. 1979. A time series approach to forecasting Australian total live-births. *Demography,* 16, 575–601.

MCDONALD, J. 1981. Modelling demographic relationships: an analysis of forecast functions for Australian births. *Journal of the American Statistical Association,* 76, 782–792.

MCDONALD, J. 1983. The emergence of countercyclical US fertility: a reassessment of the evidence. *Journal of Macroeconomics,* 5, 421–436.

MCDONALD, P. & KIPPEN, R. 1999. *Population futures for Australia: the policy alternatives.*

MCDONALD, P. & KIPPEN, R. 2011. The determinants of Australia's future demography. *In:* PRODUCTIVITY COMMISSION (ed.), *A 'sustainable' population?—Key policy issues, Roundtable Proceeding.* Commonwealth of Australia, Melbourne. http://www.pc.gov.au/__data/assets/pdf_file/0008/111041/03-population-chapter02.pdf

MCFADDEN, D. 1986. The choice theory approach to market research. *Marketing science,* 5, 275–297.

MCFADDEN, D. & TRAIN, K. 2000. Mixed MNL models for discrete response. *Journal of Applied Econometrics,* 15, 447–470.

MCKEOWN, T. 1979. *The role of medicine. Dream, mirage or Nemesis?* Basil Blackwell Publisher Ltd., Oxford.

MCKINLAY, J. B. 1972. Some approaches and problems in the study of the use of services—an overview. *Journal of Health and Social Behavior,* 13, 115–152.

MCKINLAY, J. B. & MCKINLAY, S. M. 1977. The questionable contribution of medical measures to the decline of mortality in the United States in the twentieth century. *The Milbank Memorial Fund Quarterly: Health and Society,* 55, 405–428.

MCNICOLL, G. & MAMAS, S. G. M. 1973. *The demographic situation in Indonesia,* East-West Center.

MCNICOLL, G. & SINGARIMBUN, M. 1983. *Fertility decline in Indonesia: analysis and interpretation,* National Academies.

MCPAKE, B., NORMAND, C. & SMITH, S. 2012. *Health economics: an international perspective,* Routledge.

MECHANIC, D. 1979. Correlates of physician utilization: why do major multivariate studies of physician utilization find trivial psychosocial and organizational effects? *Journal of Health and Social Behavior,* 20, 387–396.

MENDOZA-SASSI, R. & BÉRIA, J. U. 2001. Utilización de los servicios de salud: unarevisión sistemática sobre los factores relacionados. *Cadernos de SaúdePública,* 17, 819–832.
MIHAYLOVA, B., BRIGGS, A., O'HAGAN, A. & THOMPSON, S. G. 2011. Review of statistical methods for analysing healthcare resources and costs. *Health Economics,* 20, 897-916.
MIILUNPALO, S., VUORI, I., OJA, P., PASANEN, M. & URPONEN, H. 1997. Self-rated health status as a health measure: the predictive value of self-reported health status on the use of physician services and on mortality in the working-age population. *Journal of Clinical Epidemiology,* 50, 517–528.
MINKOVITZ, C. S., O'CAMPO, P. J., CHEN, Y. H. & GRASON, H. A. 2002. Associations between maternal and child health status and patterns of medical care use. *Ambulatory Pediatrics,* 2, 85–92.
MoH 2004. *Indonesia health system,* Ministry of Health, Jakarta, Indonesia.
MoH 2010. *2010–2014 Ministry of Health strategic plan,* Ministry of Health, Jakarta, Indonesia.
MOORE, G. T., BERNSTEIN, R. & BONANNO, R. A. 1972. Effect of a neighborhood health center on hospital emergency room use. *Medical Care,* 10, 240–247.
MORRIS, S., SUTTON, M. & GRAVELLE, H. 2005. Inequity and inequality in the use of health care in England: an empirical investigation. *Social Science and Medicine,* 60, 1251–1266.
MOUZA, A. M. 2002. Estimation of the total number of hospital admissions and bed requirements for 2011: the case for Greece. *Health Services Management Research,* 15, 186–192.
MUHIDIN, S. 2002. *Population of Indonesia: regional demographic scenarios using a multiregional data sources.* Ph.D diss., Rijksuniversiteit Groningen.
MUSGROVE, P. 1986. Measurement of equity in health. *World Health Statistics Quarterly,* 39, 325–335.
MUSGROVE, P., ZERAMDINI, R. & CARRIN, G. 2002. Basic patterns in national health expenditure. *Bulletin—World Health Organization,* 80, 134–142.
MUSTARD, C. A., KAUFERT, P., KOZYRSKYJ, A. & MAYER, T. 1998. Sex differences in the use of health care services. *New England Journal of Medicine,* 338, 1678–1683.
MUTRAN, E. & FERRARO, K. F. 1988. Medical need and use of services among older men and women. *Journal of Gerontology,* 43, S162–S171.
MWABU, G., AINSWORTH, M. & NYAMETE, A. 1993. Quality of medical care and choice of medical treatment in Kenya: an empirical analysis. *The Journal of Human Resources,* 28, 838–862.
NATARAJAN, S. & NIETERT, P. J. 2004. Hypertension, diabetes, hypercholesterolemia, and their combinations increased health care utilization and decreased health status. *Journal of Clinical Epidemiology,* 57, 954–961.
NATIONAL BOARD FOR PLACEMENT AND PROTECTION OF INDONESIAN WORKERS. 2012. *Placement of workers 2006–2012.* Available: http://bnp2tki.go.id/statistik-mainmenu-86/penempatan.html [Accessed November 2012].
NEWACHECK, P. W. & HALFON, N. 1986. The association between mother's and children's use of physician services. *Medical Care,* 24, 30–38.
NEWACHECK, P. W., STODDARD, J. J., HUGHES, D. C. & PEARL, M. 1998. Health insurance and access to primary care for children. *New England Journal of Medicine,* 338, 513–519.

NEWHOUSE, J. P. 1993. *Free for all? Lessons from the RAND health insurance experiment,* Harvard University Press.

NEWHOUSE, J. P., PHELPS, C. E. & SCHWARTZ, W. B. 1974. Policy options and the impact of national health insurance. *New England Journal of Medicine,* 290, 1345–1359.

NHRDC 2007. Report on 2007 basic health research. *In:* NATIONAL HEALTH RESEARCH AND DEVELOPMENT CENTRE, MINISTRY OF HEALTH (ed.), Republic of Indonesia.

NIHRD 2007. *Riset Kesehatan Dasar: Laporan Nasional 2007,* Ministry of Health, Jakarta, Indonesia.

NITISASTRO, W. 2006. *Population trends in Indonesia,* Equinox Pub.

O'BRIEN-PALLAS, L., BAUMANN, A., DONNER, G., MURPHY, G. T., LOCHHAAS-GERLACH, J. & LUBA, M. 2001. Forecasting models for human resources in health care. *Journal of Advanced Nursing,* 33, 120–129.

O'DONNELL, O. 2007. Access to health care in developing countries: breaking down demand side barriers. *Cadernos de SaúdePública,* 23, 2820–2834.

O'DONNELL, O., VAN DOORSLAER, E., RANNAN-ELIYA, R. P., SOMANATHAN, A., ADHIKARI, S. R., HARBIANTO, D., GARG, C. C., HANVORAVONGCHAI, P., HUQ, M. N. & KARAN, A. 2007. The incidence of public spending on healthcare: comparative evidence from Asia. *The World Bank Economic Review,* 21, 93–123.

O'DONNELL, O., VAN DOORSSLAER, E., WAGSTAFF, A. & LINDELOW, M. 2008. *Analyzing health equity using household survey data: a guide to techniques and their implementation,* World Bank Publications.

OMRAN, A. R. 1971. The epidemiologic transition: a theory of the epidemiology of population change. *The Milbank Memorial Fund Quarterly,* 49, 509–538.

OMRAN, A. R. 1998. The epidemiological transition revisited thirty years later. *World Health Statistics Quarterly,* 51, 99–119.

OMRAN, A. R. 2005. The epidemiologic transition: a theory of the epidemiology of population change. *Milbank Quarterly,* 83, 731–757.

ORTEGA, J. A. & PONCELA, P. 2005. Joint forecasts of Southern European fertility rates with non-stationary dynamic factor models. *International Journal of Forecasting,* 21, 539–550.

PALACIO-VIEIRA, J.-A., VILLALONGA-OLIVES, E., VALDERAS, J., HERDMAN, M., ALONSO, J. & RAJMIL, L. 2012. Predictors of the use of healthcare services in children and adolescents in Spain. *International Journal of Public Health,* 1–9.

PALMER, R. H., DONABEDIAN, A. & POVAR, G. J. 1991. *Striving for quality in health care: an inquiry into policy and practice,* Health Administration Press, Ann Arbor, Michigan.

PARKHURST, J. O. & SSENGOOBA, F. 2009. Assessing access barriers to maternal health care: measuring bypassing to identify health centre needs in rural Uganda. *Health Policy and Planning,* 24, 377–384.

PAULY, M. V. 1974. Over insurance and public provision of insurance: the roles of moral hazard and adverse selection. *The Quarterly Journal of Economics,* 88, 44–62.

PAULY, M. V. 1994. A re-examination of the meaning and importance of supplier-induced demand. *Journal of Health Economics,* 13, 369.

PENCHANSKY, R. 1976. Access to medical care. *Medical Care,* 14, 642.

PENCHANSKY, R. & THOMAS, J. W. 1981. The concept of access: definition and relationship to consumer satisfaction. *Medical Care,* 127–140.

PETERS, D. H., GARG, A., BLOOM, G., WALKER, D. G., BRIEGER, W. R. & HAFIZUR RAHMAN, M. 2008. Poverty and access to health care in developing countries. *Annals of the New York Academy of Sciences,* 1136, 161–171.

PHELPS, C. E. 1997. *Health economics,* Addison-Wesley, Reading, MA.

PHILLIPS, S. 2005. Defining and measuring gender: a social determinant of health whose time has come. *International Journal for Equity in Health,* 4, 11.

PILLAI, R. K., WILLIAMS, S. V., GLICK, H. A., POLSKY, D., BERLIN, J. A. & LOWE, R. A. 2003. Factors affecting decisions to seek treatment for sick children in Kerala, India. *Social Science & Medicine,* 57, 783–790.

PORTES, A., KYLE, D. & EATON, W. W. 1992. Mental illness and help-seeking behavior among Mariel Cuban and Haitian refugees in South Florida. *Journal of Health and Social Behavior,* 283–298.

PRADHAN, M., SAADAH, F. & SPARROW, R. 2007. Did the health card program ensure access to medical care for the poor during Indonesia's economic crisis? *The World Bank Economic Review,* 21, 125–150.

PREGIBON, D. 1981. Logistic regression diagnostics. *The Annals of Statistics,* 4, 705–724.

PRENTICE, J. C. 2006. Neighborhood effects on primary care access in Los Angeles. *Social Science & Medicine,* 62, 1291–1303.

QIAN, D. F., PONG, R. W., YIN, A. T., NAGARAJAN, K. V. & MENG, Q. Y. 2009. Determinants of health care demand in poor, rural China: the case of Gansu Province. *Health Policy and Planning,* 24, 324–334.

RAGHUPATHY, S. 1996. Education and the use of maternal health care in Thailand. *Social Science & Medicine,* 43, 459–471.

RANKIN, S. L., HUGHES-ANDERSON, W., HOUSE, A. K., HEATH, D. I., AITKEN, R. J. & HOUSE, J. 2001. Costs of accessing surgical specialists by rural and remote residents. *ANZ Journal of Surgery,* 71, 544–547.

REINHARDT, U. E. 2003. Does the aging of the population really drive the demand for health care? *Health Affairs,* 22, 27–39.

REVELT, D. & TRAIN, K. 1998. Mixed logit with repeated choices: households' choices of appliance efficiency level. *Review of Economics and Statistics,* 80, 647–657.

RICHARDSON, J. R. J. & MCKIE, J. 1999. *Ageing and the cost of health services,* Centre for Health Program Evaluation.

RILEY, A. W., FINNEY, J. W., MELLITS, E. D., STARFIELD, B., KIDWELL, S., QUASKEY, S., CATALDO, M. F., FILIPP, L. & JON, P. S. 1993. Determinants of children's health care use: an investigation of psychosocial factors. *Medical Care,* 31, 767–783.

RIVNYAK, M. H., WAN, T. T. H., STEGALL, M. H., JACOBS, M. & LI, S. 1989. Ambulatory care use among the non-institutionalized elderly. *Research on Aging,* 11, 292–311.

ROGERS, A. & LITTLE, J. S. 1994. Parameterizing age patterns of demographic rates with the multi-exponential model schedule. *Mathematical Population Studies,* 4, 175–195.

ROKX, C., GILES, J., SATRIAWAN, E., MARZOEKI, P. & HARIMURTI, P. 2010. *New insights into the provision of health services in Indonesia: a health workforce study,* World Bank Publications.

ROKX, C., SCHIEBER, G. & HARIMURTI, P. 2009. *Health financing in Indonesia: a reform road map,* World Bank Publications.

ROSENBACH, M. L., IRVIN, C. & COULAM, R. F. 1999. Access for low-income children: is health insurance enough? *Pediatrics,* 103, 1167–1174.

ROSENSTOCK, I. M., STRECHER, V. J. & BECKER, M. H. 1988. Social Learning Theory and the Health Belief Model. Health Education & Behavior, 15, 175-183.

ROSENSTOCK, I. M. 1966. Why people use health services. *The Milbank Memorial Fund Quarterly,* 44, 94–127.

ROSNER, T. T., NAMAZI, K. H. & WYKLE, M. L. 1988. Physician use among the old-old: factors affecting variability. *Medical Care,* 26, 982–991.

ROSS, C. E. 1995. Reconceptualizing marital status as a continuum of social attachment. *Journal of Marriage and the Family,* 129–140.

ROSS, C. E., MIROWSKY, J. & GOLDSTEEN, K. 1990. The impact of the family on health: the decade in review. *Journal of Marriage and the Family,* 52, 1059–1078.

SAHN, D. E. & YOUNGER, S. D. 2000. Expenditure incidence in Africa: microeconomic evidence. *Fiscal Studies,* 21, 329–347.

SAHN, D. E., YOUNGER, S. D. & GENICOT, G. 2003. The demand for health care services in rural Tanzania. *Oxford Bulletin of Economics and Statistics,* 65, 241–259.

SCHEFFLER, R. M., LIU, J. X., KINFU, Y. & DAL POZ, M. R. 2008. Forecasting the global shortage of physicians: an economic-and-needs-based approach. *Bulletin of the World Health Organization,* 86, 516–523B.

SCHOFIELD, D. J. & EARNEST, A. 2006. Demographic change and the future demand for public hospital care in Australia, 2005 to 2050. *Australian Health Review,* 30, 507–515.

SCHWARTZ, J. B., AKIN, J. S. & POPKIN, B. M. 1988. Price and income elasticity of demand for modern health care: the case of infant delivery in the Philippines. *The World Bank Economic Review,* 2, 49–76.

SCOTT, J. C., CONNER, D. A., VENOHR, I., GADE, G., MCKENZIE, M., KRAMER, A. M., BRYANT, L. & BECK, A. 2004. Effectiveness of a group outpatient visit model for chronically ill older health maintenance organization members: a 2-year randomized trial of the cooperative health care clinic. *Journal of the American Geriatrics Society,* 52, 1463–1470.

SCOTT, L. J. & FREESE, J. 2006. Regression models for categorical dependent variables using STATA. College Station, TX: Stata Press.

SEGALL, M., TIPPING, G., LUCAS, H., DUNG, T. V., TAM, N. T., VINH, D. X. & HUONG, D. L. 2002. Economic transition should come with a health warning: the case of Vietnam. *Journal of Epidemiology and Community Health,* 56, 497–505.

SESHAMANI, M. & GRAY, A. 2004. Ageing and health-care expenditure: the red herring argument revisited. *Health Economics,* 13, 303–314.

SHAH, N. M. 2012. Socio-demographic transitions among nationals of GCC countries: implications for migration and labour force trends. *Migration and Development,* 1, 138–148.

SILLS, M. R., SHETTERLY, S., XU, S., MAGID, D. & KEMPE, A. 2007. Association between parental depression and children's health care use. *Pediatrics,* 119, e829–e836.

SILVER, E. J. & STEIN, R. E. K. 2001. Access to care, unmet health needs, and poverty status among children with and without chronic conditions. *Ambulatory pediatrics,* 1, 314–320.

SIMMS, C. & ROWSON, M. 2003. Reassessment of health effects of the Indonesian economic crisis: donors versus the data. Lancet, 361, 1382-1385.

SINQUEFIELD, J. & KARTOYO, A. 1977. Using retrospective mortality data to test the applicability of model life tables for Indonesia. *Majalah Demografi Indonesia,* 4, 25.

SKOUFIAS, E. & SURYAHADI, A. 2000. Changes in Household Welfare, Poverty and Inequality During the Crisis. *Bulletin of Indonesian Economic Studies*, 36, 97-114.

SMITH, S. K., TAYMAN, J. & SWANSON, D. A. 2001. *State and local population projections,* Kluwer Academic, Plenum Publications.

SOSA-RUBÍ, S. G., GALÁRRAGA, O. & HARRIS, J. E. 2009. Heterogeneous impact of the 'Seguro Popular' program on the utilization of obstetrical services in Mexico, 2001–2006: a multinomial probit model with a discrete endogenous variable. *Journal of Health Economics,* 28, 20–34.

SPARROW, R. 2008. Targeting the poor in times of crisis: the Indonesian health card. *Health Policy and Planning,* 23, 188–199.

SPARROW, R., SURYAHADI, A., WIDYANTI, W., MONITORING, S. & UNIT, E. R. 2010. *Social health insurance for the poor: targeting and impact of Indonesia's Askeskin program,* Smeru Research Institute.

STARFIELD, B., HANKIN, J., STEINWACHS, D., HORN, S., BENSON, P., KATZ, H. & GABRIEL, A. 1985. Utilization and morbidity: random or tandem? *Pediatrics,* 75, 241–247.

STEVENS, J. A., BALLESTEROS, M. F., MACK, K. A., RUDD, R. A., DECARO, E. & ADLER, G. 2012. Gender differences in seeking care for falls in the aged medicare population. *American Journal of Preventive Medicine,* 43, 59–62.

STEWART, D. K., FINLAYSON, G., MACWILLIAM, L. & ROOS, N. 2002. *Projecting hospital bed needs for 2020.* Manitoba Centre for Health Policy, University of Manitoba.

STOCK, R. 1983. Distance and the utilization of health facilities in rural Nigeria. *Social Science & Medicine,* 17, 563–570.

STRAUSS, J. F., WITOELAR, F., SIKOKI, B. & WATTIE, A. M. 2009. The fourth wave of the Indonesia family life survey (IFLS4): Overview and Field Report. WR-675/1-NIA/NICHD

STRUNK, B. C. & GINSBURG, P. B. 2002. Aging plays limited role in health care cost trends. *Data Bulletin (Center for Studying Health System Change),* 1.

STRUNK, B. C., GINSBURG, P. B. & BANKER, M. I. 2006. The effect of population aging on future hospital demand. *Health Affairs,* 25, w141–w149.

SUOMINEN-TAIPALE, A., MARTELIN, T., KOSKINEN, S., HOLMEN, J. & JOHNSEN, R. 2006. Gender differences in health care use among the elderly population in areas of Norway and Finland. A cross-sectional analysis based on the HUNT study and the FINRISK senior survey. *BMC Health Services Research,* 6, 110.

SURYAHADI, A., SUMARTO, S. & PRITCHETT, L. 2003. Evolution of Poverty During the Crisis in Indonesia. *Asian Economic Journal*, 17, 221-241.

SUTRISNA, B., KRESNO, S., UTOMO, B., REINGOLD, A. & HARRISON, G. 1993. Care-seeking for fatal illnesses in young children in Indramayu, West Java, Indonesia. *The Lancet,* 342, 787–789.

SUTTON, M., CARR-HILL, R., GRAVELLE, H. & RICE, N. 1999. Do measures of self-reported morbidity bias the estimation of the determinants of health care utilisation? *Social Science & Medicine,* 49, 867–878.

TATE, R. B., MACWILLIAM, L. & FINLAYSON, G. S. 2005. A methodology for estimating hospital bed need in Manitoba in 2020. *Canadian Journal on Aging/Revue canadienne du vieillissement,* 24, 141–151.

TESSLER, R. & MECHANIC, D. 1978. Factors affecting children's use of physician services in a prepaid group practice. *Medical Care,* 33–46.

TITALEY, C., DIBLEY, M., AGHO, K., ROBERTS, C. & HALL, J. 2008. Determinants of neonatal mortality in Indonesia. *BMC Public Health,* 8, 232.

TITALEY, C. R., DIBLEY, M. J., ROBERTS, C. L., HALL, J. & AGHO, K. 2010. Iron and folic acid supplements and reduced early neonatal deaths in Indonesia. *Bulletin of the World Health Organization,* 88, 500–508.

TRAIN, K. & SONNIER, G. 2005. Mixed logit with bounded distributions of correlated partworths. *In:* SCARPA, R. & ALBERINI, A. (eds.), *Applications of simulation methods in environmental and resource economics,* Springer, Boston, pp. 117–134.

TRAIN, K. E. 1998. Recreation demand models with taste differences over people. *Land Economics,* 74, 230–239.

TRUE, W. R., ROMEIS, J. C., HEATH, A. C., FLICK, L. H., SHAW, L., EISEN, S. A., GOLDBERG, J. & LYONS, M. J. 1997. Genetic and environmental contributions to healthcare need and utilization: a twin analysis. *Health Services Research,* 32, 37.

TRUJILLO, A. J. 2003. Medical care use and selection in a social health insurance with an equalization fund: evidence from Colombia. *Health Economics,* 12, 231–246.

UMBERSON, D. 1987. Family status and health behaviors: social control as a dimension of social integration. *Journal of Health and Social Behavior,* 28, 306–319.

UMBERSON, D. 1992. Gender, marital status and the social control of health behavior. *Social Science & Medicine,* 34, 907–917.

UNITED NATIONS 1983. *Manual X: indirect techniques for demographic estimation.* United Nations Publication.

UNITED NATIONS 2011. *World population prospects: the 2010 revision.* Department of Economic and Social Affairs Population Division.

VAN DOORSLAER, E., O'DONNELL, O., RANNAN-ELIYA, R. P., SOMANATHAN, A., ADHIKARI, S. R., GARG, C. C., HARBIANTO, D., HERRIN, A. N., HUQ, M. N. & IBRAGIMOVA, S. 2007. Catastrophic payments for health care in Asia. *Health Economics,* 16, 1159–1184.

VAN DOORSLAER, E., WAGSTAFF, A., VAN DER BURG, H., CHRISTIANSEN, T., DE GRAEVE, D., DUCHESNE, I., GERDTHAM, U.-G., GERFIN, M., GEURTS, J., GROSS, L., HÄKKINEN, U., JOHN, J., KLAVUS, J., LEU, R. E., NOLAN, B., O'DONNELL, O., PROPPER, C., PUFFER, F., SCHELLHORN, M., SUNDBERG, G. & WINKELHAKE, O. 2000. Equity in the delivery of health care in Europe and the US. *Journal of Health Economics,* 19, 553–583.

VERBRUGGE, L. & WINGARD, D. 1987. Sex differentials in health and mortality. *Women & Health,* 12, 103.

WADDINGTON, C. J. & ENYIMAYEW, K. A. 1989. A price to pay: the impact of user charges in ashanti-akim district, Ghana. *The International Journal of Health Planning and Management,* 4, 17–47.

WAGSTAFF, A. 1989. Econometric studies in health economics: a survey of the British literature. *Journal of Health Economics,* 8, 1–51.

WAGSTAFF, A. & VAN DOORSLAER, E. 2000. Measuring and testing for inequity in the delivery of health care. *The Journal of Human Resources,* 35, 716–733.

WAGSTAFF, A., PACI, P. & VAN DOORSLAER, E. 1991. On the measurement of inequalities in health. *Social Science & Medicine,* 33, 545–557.

WAGSTAFF, A., VAN DOORSLAER, E. & WATANABE, N. 2003. On decomposing the causes of health sector inequalities with an application to malnutrition inequalities in Vietnam. *Journal of Econometrics,* 112, 207–223.

WAITE, L. J. 1995. Does marriage matter? *Demography,* 32, 483–507.

WALDRON, I. 1983. Sex differences in illness incidence, prognosis and mortality: issues and evidence. *Social Science & Medicine,* 17, 1107–1123.

WARREN, J. L., MARIOTTO, A. B., MEEKINS, A., TOPOR, M. & BROWN, M. L. 2008. Current and future utilization of services from medical oncologists. *Journal of Clinical Oncology,* 26, 3242–3247.

WATANABE, Y. & TSUBO, T. 1995. Forecasting Japanese health futures with the BFT: A demand-side approach. Futures, 27, 959-966.

WATERS, H. R. 1999. Measuring the impact of health insurance with a correction for selection bias—a case study of Ecuador. Health Economics, 8, 473-483.

WATERS, H. R. 2000. Measuring equity in access to health care. *Social Science & Medicine,* 51, 599–612.

WERBLOW, A., FELDER, S. & ZWEIFEL, P. 2007. Population ageing and health care expenditure: a school of 'red herrings'? *Health Economics,* 16, 1109–1126.

WHITEHEAD, M. 1992. The concepts and principles of equity and health. *International Journal of Health Services,* 22, 429–445.

WHO 2006. *The world health report 2006: working together for health.* World Health Organization.

WHO 2009. *Global health risks: mortality and burden of disease attributable to selected major risks,* World Health Organization.

WHO 2012. World Health Statistics 2012. Who Health Organization.

WISEMAN, V., SCOTT, A., CONTEH, L., MCELROY, B. & STEVENS, W. 2008. Determinants of provider choice for malaria treatment: experiences from the Gambia. *Social Science & Medicine,* 67, 487–496.

WOLFE, B. L. 1980. Children's utilization of medical care. *Medical Care,* 18, 1196–1207.

WOLINSKY, F. D. 1978. Assessing the effects of predisposing, enabling, and illness-morbidity characteristics on health service utilization. *Journal of Health and Social Behavior,* 19, 384–396.

WOLINSKY, F. D. 1981. The problems for academic and entrepreneurial research in the use of health services: the case of unstable structural relationships. *The Sociological Quarterly,* 22, 207–223.

WOLINSKY, F. D., ARNOLD, C. L. & NALLAPATI, I. V. 1988. Explaining the declining rate of physician utilization among the oldest-old. *Medical Care,* 26, 544–553.

WOLINSKY, F. D., MOSELY II, R. R. & COE, R. M. 1986. A cohort analysis of the use of health services by elderly Americans. *Journal of Health and Social Behavior,* 27, 209–219.

WOODWARD, C. A., BOYLE, M. H., OFFORD, D. R., CADMAN, D. T., LINKS, P. S., MUNROE-BLUM, H., BYRNE, C. & THOMAS, H. 1988. Ontario child health study: patterns of ambulatory medical care utilization and their correlates. *Pediatrics,* 82, 425–434.

WORLD BANK 2008. Investing in Indonesia's health: challenges and opportunities for future public spending. *Health Public Expenditure Review.* The World Bank Office Jakarta

WYKE, S. & FORD, G. 1992. Competing explanations for associations between marital status and health. *Social Science & Medicine,* 34, 523–532.

XUE, J. L., MA, J. Z., LOUIS, T. A. & COLLINS, A. J. 2001. Forecast of the number of patients with end-stage renal disease in the United States to the year 2010. *Journal of the American Society of Nephrology,* 12, 2753–2758.

YIP, W. C., WANG, H. & LIU, Y. L. 1998. Determinants of patient choice of medical provider: a case study in rural China. *Health Policy and Planning,* 13, 311–322.

YODER, R. A. 1989. Are people willing and able to pay for health services? *Social Science & Medicine,* 29, 35–42.

YU, S. T., CHANG, H. Y., LIN, M. C. & LIN, Y. H. 2009. Agreement between self-reported and health insurance claims on utilization of health care: a population study. *Journal of Clinical Epidemiology,* 62, 1316–1322.

ZWEIFEL, P., FELDER, S. & WERBLOW, A. 2004. Population ageing and health care expenditure: new evidence on the 'red herring'. *The Geneva Papers on Risk and Insurance—Issues and Practice,* 29, 652–666.

ZWEIFEL, P. & MANNING, W. G. 2000. Moral hazard and consumer incentives in health care. *Handbook of Health Economics,* 1, 409–459.

Appendices

Appendix 1. Description of Healthcare Providers

Type of provider	Provider	Description	Ownership
Traditional practice	Traditional practice	Healthcare services and alternative medicine practiced by shaman, wiseman, kyai, Chinese herbalist, masseur, acupuncturist, paranormal practitioner, etc. Also included in this category are traditional midwives; that is, an alternative healthcare service provided by traditional healers specialising in pregnancy and delivery, both those who were trained and untrained by Ministry of Health.	Traditional
Nurse/paramedic/ midwife practice	Nurse, private practice	A nurse providing a primary healthcare service professionally in a private practice, without receiving a salary for this service from the government. The nurse can have a dual practice, where the other is working in a clinic, hospital or health centre. In this case, the service is counted as a clinic, hospital or health centre provider, not as nurse practice.	Private
	Paramedic practice	Healthcare professionals such as optometrists, chiropractors and physiotherapists who practice individually. This does not refer to healthcare professionals who work in emergency services as defined in Australia and other countries.	Private
	Midwife and village midwife practice	A midwife whose primary professional activity is private and who does not receive a salary from the government for his or her service. Similar to nurses and doctors, midwives commonly have a dual practice. When a midwife is providing a service in a health facility and receives a salary for that service, this is not considered as midwife practice. A village midwife privately works in specific villages.	Private
Physician practice	Physician practice	A medical doctor (either GPs or medical specialists including dentist) whose primary activity is providing care privately and individually and who does not receive a salary from the government for his or her service. Dentists are included in this category. However, a medical doctor can also work in a health private or public provider, or in both.	Private
Health centre	Health centre	A public healthcare provider is usually located in the capital of a sub-district. Many kinds of health professionals work in health centres, including GPs, medical specialists, dentists, midwives and nurses.	Public
	Auxiliary health centre	Public health sub-centre, usually located in the village. Administratively, it is under the supervision of a health centre. Its main health professionals are supplied by the health centre.	Public
Hospital/Clinic	Public hospital	Public hospital, usually located at the district and province level, including military hospitals or state-owned enterprise hospitals.	Public
	Private hospital	Private hospital, not bound to political administration.	Private
	Clinic	Service for outpatient healthcare, managed by a company, organisation, foundation or privately.	Private

Appendix 2. Diagnostic Test for Logistic Regression

The model specification is examined using a *link test* to investigate any additional predictors that might be statistically significant. The Box-Tidwell model (Box and Tidwell, 1966), which transforms independent variables using power transformations to find the best power for model fit, is used. The variable of consumption has been converted into dummy variables representing four quartiles, so that the Box-Tidwell test is not necessary.

The goodness of fit of the model was tested by investigating the predicted probability methods. A Hosmer-Lemeshow test shows that the model fits that data well. Another test was conducted to investigate the predictability power of the model by comparing the predicted and observed outputs.

Table A.1. Diagnostic tests of logit regression

Test	Full model	Male	Female
Log-likelihood	-6161.69	-2321.93	-3819.59
Pseudo R^2	0.1034	0.1179	0.0799
Hosmer-Lemeshow	p-value = 0.1141	p-value = 0.9401	p-value = 0.5311
Correct classification	83.80%	88.06%	80.18%

The model was checked against multicolinearity by looking at the VIF, which is an indication of the effect of colinearity on standard error inflation.

Table A.2. Tests of multicolinearity among variables

Variable	VIF (Variance inflation factor)	Tolerance	R^2
Visit	1.09	0.918	0.082
Age	36.10	0.028	0.972
Age square	33.73	0.029	0.970
Female	1.57	0.638	0.362
Married	1.15	0.866	0.134
Household head	1.93	0.517	0.483
Household size	1.17	0.855	0.146
Islam	1.08	0.929	0.071
Javanese	1.23	0.815	0.185
Education	1.28	0.782	0.218
Working	1.2	0.831	0.169
Facility knowledge	1.26	0.792	0.208
Insured	1.03	0.972	0.028
Rural	1.21	0.826	0.174
Java and Bali	1.28	0.782	0.218
Health condition	1.15	0.872	0.128
Severity of illness	1.14	0.881	0.119
Income	4.49	0.223	0.777
Income square	3.88	0.258	0.742
Stove	1.21	0.827	0.173
Mean	5.11		

Appendix 3. Health Insurance Endogeneity Test

Bivariate and univariate probit were employed to investigate the possible adverse selection of health insurance, as done by Waters (1999).

The primary equation is formulated as follows:

$$M_i^* = \beta X_i + \alpha y_i + \epsilon_i \tag{4.3.1}$$

Where M_i= 1 (individual I seeks healthcare) if M_i^*>0 and M_i= 0 (individual I does not seek healthcare) otherwise. y_i^* represents the inclination for individuals to have positive values, X is the exogenous variables.

The secondary equation is formulated as follows:

$$y_i^* = \gamma X_i + \delta y_i + \mu_i \tag{4.3.2}$$

Where y_i= 1 (individual *i selected positively*) if y_i^*>0 and y_i= 0 (individual I selected negatively) otherwise. Z is one or more identifying variables.

This type of test requires the identification of appropriate identifying variables (*Z*); that is, variables that are present in the secondary equation, but absent in the primary equation, and that have an impact on the suspected endogenous variable, but are not directly related to the dependent variable in the primary equation (health visit).

As in Waters (1999), three methods were employed for the test of identifying variables:

1. Significance of impact of the endogenous variables, assessed by regressing health insurance subscription into all proposed independent variables.
2. Insignificance impact of identifying variables to health visit, assessed by using univariate probit of the primary equation with all dependent variables included.
3. Likelihood ratio test to compare two primary equations. These are a primary equation with the proposed identifying variable replacing the suspected endogenous variable (health insurance), and a second primary equation with the predicted value of health insurance subscription substituting the endogenous variable. A likelihood ratio test was conducted to compare these two equations and the insignificant difference in the likelihood indicates the appropriateness of the identifying

variables. The three identifying variables were proposed as ethnicity, religion and cooking method.

Table A.3. Result of the endogeneity test

Test	Religion	Ethnicity	Cooking method
1. Significance impact to health insurance	*p*-value=0.000	*p*-value=0.058	*p*-value=0.000
2. Significance impact to health visit	*p*-value=0.556	*p*-value=0.125	*p*-value=0.106
3. Likelihood ratio of two equations		rho =0.200	

Since the association between ethnicity and health insurance subscription is weak (p=0.058), the model subsequently used only two identifying variables (religion and cooking method). The following methods were then used to test whether health insurance is endogenous:

1. The significance of *rho* in the bivariate probit. This method tests whether the covariance between primary and secondary equation is significantly different from zero. If this is the case, unobservable factors (in these models, represented by identifying variables; that is, religion and cooking method) influence health insurance subscription choice and are also influencing the decision to visit healthcare providers. In other words, health insurance is endogenous.

2. The second test looks at the influence of predicted values from the secondary equation when inserted into the primary equation. This tests whether the unobservable factors also explain the variation in decision to visit healthcare providers. A significantly non-zero coefficient of predicted health insurance indicates that health insurance is endogenous.

3. Comparison of univariate and bivariate probit. The effect of endogeneity is detected if there is a large difference in the coefficient. Change in the sign of the coefficient and change in the significance of the coefficient shows the present of endogeneity.

The results of the two tests are presented in Table A.4. The test of endogeneity shows that health insurance is exogenous.

Table A.4. Results of endogeneity test of health insurance

Test	Adult 15+ model	Adult male	Adult female
1. Covariance (rho) of primary and secondary equation	Rho=-0.069 (p-value=0.170)	Rho=-0.099 (p-value=0.229)	Rho=-0.067 (p-value=0.296)
2. Coefficient of predicted health insurance	*p*-value=0.244	*p*-value=0.374	*p*-value=0.430
3. Comparison of univariate and bivariate coefficient of insurance	Univariate: *p*-value=0.000 β= 0.256 Bivariate: p-value=0.000 β =0.323	Univariate: *p*-value=0.005 β= 0.131 Bivariate: *p*-value=0.036 β= 0.280	Univariate: *p*-value=0.000 β= 0.256 Bivariate: p-value=0.001 β =0.356

Appendix 4. Result of Logistic Regression Model of Healthcare Utilisation for Adult 15+ Model (15 Years and Above)

Variable	Adult 15+	
	Odds ratio	SE
Demographic		
Age	1.006	0.555
Age square	1.000	0.000
Sex	1.725***	0.101
Marital status	1.347***	0.069
Householder status	1.182***	0.076
Religion	1.029	0.075
Ethnicity	1.016	0.051
Household size	0.994	0.008
Social economic		
Education		
No education		
Primary	1.353**	0.118
Secondary	1.374**	0.135
Tertiary	1.493**	0.183
Facility knowledge	1.078***	0.014
Working	1.170**	0.057
Insured	1.424***	0.070
Economic status:		
1st Quartile (lowest)	1.000	
2nd Quartile	1.145*	0.077
3rd Quartile	1.376***	0.094
4th Quartile (highest)	1.357***	0.099
Region of residence	1.145**	0.077
Island of residence	1.376*	0.094
Health need		
Self-rated health	1.836***	0.095
Severity of illness	2.971***	0.139
Constant	0.011***	0.002
Sample (N)	**16,280**	

Notes: Significant level: *** $p<0.001$, ** $p<0.01$, * $p<0.05$

Appendix 5. Standardised Regression of Children, Adult and Elderly Models

Variables	Fully standardised coefficient		
	Children (<15 yrs)	Adult (15–69 yrs)	Elderly (70+ yrs)
Demographic			
Age	-0.24	0.05	-0.32
Age square	0.05	0.04	0.34
Sex	-0.03	0.13	0.16
Marital status		0.08	0.03
Householder status		0.04	0.06
Religion	0.00	0.00	0.04
Ethnicity	-0.01	0.00	-0.03
Household size		-0.01	-0.07
Number of children	-0.05		
Social Economic			
Education			
No education		Ref	Ref
Primary		0.08	0.05
Secondary		0.08	0.06
Tertiary		0.06	0.04
Facility knowledge		0.07	0.13
Working		0.04	-0.09
Insured		0.08	0.08
Economic status:			
1st Quartile (lowest)	Ref	Ref	Ref
2nd Quartile	0.03	0.02	0.06
3rd Quartile	0.08	0.06	0.13
4th Quartile (highest)	0.07	0.07	0.04
Region of residence	-0.04	0.04	0.05
Island of residence	0.10	0.03	0.01
Health Needs			
Self-rated health	0.09	0.12	0.03
Severity of illness	0.31	0.27	0.25
Chronic disease			0.24
Carer's Characteristics			
Carer's age	-0.02		
Carer's sex	-0.01		
Carer's education	0.03		
Carer's marital status	0.00		
Carer's employment	-0.01		
Sample (N)	**8,316**	**14,775**	**753**

Appendix 6. Result of Logistic Regression Model of Healthcare Utilisation for Male and Female Children (<15 years)

Variable	Male Children (<15 yrs)		Female Children (<15 years)	
	Odds ratio	SE	Odds ratio	SE
Demographic				
Age	0.859***	0.027	0.922**	0.031
Age square	1.005*	0.002	0.999	0.003
Religion	0.970	0.123	1.085	0.144
Ethnicity	0.931	0.077	0.993	0.086
Number of children	0.897*	0.044	0.897*	0.044
Social Economic				
Economic status:				
1st Quartile (lowest)				
2nd Quartile	1.445**	0.179	0.934	0.115
3rd Quartile	1.606***	0.196	1.343**	0.165
4th Quartile (highest)	1.548**	0.200	1.194	0.154
Region of residence	0.892	0.072	0.783**	0.065
Island of residence	1.633***	0.138	1.370***	0.119
Health Needs				
Self-rated health	1.766***	0.172	1.699***	0.170
Severity of illness	3.822***	0.317	3.490***	0.304
Carer's Characteristics				
Carer's age	0.987	0.087	0.867	0.079
Carer's sex	0.883	0.142	1.034	0.183
Carer's education	1.114	0.067	1.086	0.068
Carer's employment	0.892	0.071	0.998	0.083
Constant	0.228	0.075	0.237	0.082
Sample (N)	**4,184**		**3,952**	

Notes: Significant level: *** p<0.001, ** p<0.01, * p<0.05

Appendix 7. Estimates of Average Marginal Effect for Adult Male and Adult Female Models*

Variable	Adult male (15–69 yrs)		Adult female (15–69yrs)	
	AME	SE	AME	SE
Demographic				
Age	0.0019***	0.0004	0.0013**	0.0004
Marital status	0.0174	0.0136	0.0729***	0.0127
Householder status	0.0072	0.0144	0.0535***	0.0157
Religion	0.0060	0.0127	0.0009	0.0146
Ethnicity	-0.0071	0.0086	0.0086	0.0100
Household size	-0.0019	0.0015	0.0006	0.0016
Social Economic				
Education				
No education	Reference		Reference	
Primary	0.0576***	0.0137	0.0279	0.0161
Secondary	0.0639***	0.0150	0.0254	0.0181
Tertiary	0.1026***	0.0212	0.0136	0.0233
Facility knowledge	0.0068**	0.0023	0.0118***	0.0027
Working	0.0078	0.0107	0.0260**	0.0092
Insured	0.0217*	0.0087	0.0671***	0.0098
Economic status:				
1st Quartile (lowest)	Reference		Reference	
2nd Quartile	0.0111	0.0112	0.0195	0.0124
3rd Quartile	0.0247	0.0117	0.0568***	0.0132
4th Quartile (highest)	0.0235	0.0126	0.0539***	0.0142
Region of residence	0.0140	0.0086	0.0260**	0.0097
Island of residence	0.0102	0.0090	0.0245*	0.0103
Health Needs				
Self-rated health	0.0632***	0.0092	0.1028***	0.0101
Severity of illness	0.1403***	0.0080	0.1443***	0.0089
Number of observations	6,846		7,929	

Notes *Since the Adult Male and Adult Female models above are built upon different sample (males only and females only, respectively), the magnitude of probability of utilising healthcare between sexes cannot be compared directly. For example, it is not known from both models above whether the effect of sex is higher for males than for female, as this is dependent on the endowment value of utilisation. Therefore, for the purpose of comparison, the significant level of the AME provides an approximation of the contribution of each variable, but not the magnitude of these contributions. Discussion is thus based on the Adult model, not on the Adult Male and Adult Female models.

Appendix 8. Predicted Probability of Utilisation Rate among the Insured and Uninsured across Income Quartiles for Adults

Income quartile	Insured			Uninsured		
	Predicted probability	95% CI Lower bound	95% CI Upper bound	Predicted probability	95% CI Lower bound	95% CI Upper bound
Q1 (lowest)	0.185	0.168	0.202	0.141	0.129	0.153
Q2	0.201	0.184	0.217	0.154	0.142	0.165
Q3	0.227	0.210	0.245	0.176	0.164	0.188
Q4 (highest)	0.229	0.211	0.247	0.177	0.164	0.190

Appendix 9. Regression Estimates of the Chronic Disease Model among Adults Aged 40 and Above

Variable	Adult 40+	
	Odds ratio	SE
Demographic		
Age	1.029	0.030
Age square	1.000	0.000
Sex	1.713	0.195
Marital status	1.301***	0.133
Householder status	1.350**	0.144
Religion	1.029	0.107
Ethnicity	1.214**	0.089
Household size	0.976*	0.012
Social Economic		
Education		
No education		
Primary	1.308**	0.128
Secondary	1.269	0.156
Tertiary	1.620**	0.278
Facility knowledge	1.085***	0.021
Working	1.174*	0.087
Insured	1.357***	0.097
Economic status:		
1^{st} Quartile (lowest)	1.000	
2^{nd} Quartile	1.149	0.112
3^{rd} Quartile	1.412**	0.140
4^{th} Quartile (highest)	1.432**	0.153
Region of residence	1.107	0.079
Island of residence	0.993	0.075
Health Needs		
Self-rated health	1.836***	0.095
Severity of illness	2.971***	0.139
Chronic diseases	1.936***	0.129
Constant	0.011***	0.002
Sample (N)	**6,631**	

Appendix 10. Projected Indonesian Population, 2010–2025 (in thousands) - Low Fertility Scenario

Age group	Male				Female				Male + Female			
	2010	2015	2020	2025	2010	2015	2020	2025	2010	2015	2020	2025
0	2,339	2,380	2,140	1,896	2,275	2,044	1,810	2,275	4,552	4,655	4,183	3,706
1–4	9,731	9,293	9,456	8,485	8,802	9,056	8,141	8,802	18,920	18,096	18,513	16,627
5–9	12,393	12,136	11,591	11,794	11,674	11,463	10,985	11,304	24,067	23,599	22,576	23,099
10–14	12,071	12,367	12,115	11,570	11,394	11,657	11,449	10,973	23,465	24,024	23,564	22,544
15–19	10,986	12,036	12,337	12,086	10,626	11,374	11,639	11,434	21,612	23,410	23,977	23,520
20–24	10,234	10,937	11,987	12,287	10,354	10,597	11,348	11,617	20,588	21,534	23,335	23,904
25–29	11,003	10,181	10,886	11,932	11,053	10,317	10,566	11,319	22,056	20,498	21,452	23,251
30–34	10,298	10,943	10,132	10,834	10,227	11,004	10,280	10,533	20,525	21,948	20,412	21,367
35–39	9,664	10,229	10,880	10,073	9,488	10,169	10,952	10,238	19,153	20,397	21,832	20,311
40–44	8,614	9,571	10,143	10,788	8,489	9,412	10,100	10,888	17,103	18,983	20,243	21,677
45–49	7,279	8,478	9,437	10,000	7,254	8,385	9,315	10,010	14,532	16,863	18,751	20,010
50–54	6,071	7,085	8,273	9,208	5,895	7,116	8,250	9,185	11,966	14,201	16,523	18,394
55–59	4,554	5,800	6,793	7,931	4,190	5,723	6,939	8,073	8,744	11,523	13,732	16,004
60–64	3,030	4,224	5,404	6,329	3,241	3,998	5,498	6,702	6,271	8,222	10,902	13,031
65–69	2,303	2,682	3,764	4,816	2,555	2,994	3,734	5,179	4,858	5,677	7,497	9,995
70–74	1,585	1,890	2,218	3,113	1,992	2,226	2,654	3,356	3,577	4,116	4,872	6,469
75–79	872	1,152	1,384	1,625	1,175	1,567	1,800	2,195	2,047	2,719	3,184	3,820
80–84	498	522	690	829	685	779	1,083	1,288	1,183	1,301	1,773	2,118
85–89	189	221	225	298	264	347	420	615	453	569	645	913
90–94	66	55	59	60	111	92	132	171	177	147	191	232
95–99	34	11	8	9	65	24	22	35	98	35	30	43
100+	3	6	5	5	6	15	16	18	10	20	21	23
Total	**123,818**	**132,201**	**139,928**	**145,969**	**122,141**	**130,336**	**138,282**	**145,088**	**245,959**	**262,537**	**278,210**	**291,056**

Appendix 11. Projected Indonesian Population, 2010–2025 (in thousands) - Medium Fertility Scenario

Age group	Male				Female				Male + Female			
	2010	2015	2020	2025	2010	2015	2020	2025	2010	2015	2020	2025
0	2,339	2,451	2,354	2,254	2,213	2,343	2,248	2,152	4,552	4,794	4,602	4,406
1–4	9,731	9,293	9,739	9,335	9,189	8,802	9,327	8,957	18,920	18,096	19,066	18,292
5–9	12,393	12,136	11,591	12,147	11,674	11,463	10,985	11,642	24,067	23,599	22,576	23,789
10–14	12,071	12,367	12,115	11,570	11,394	11,657	11,449	10,973	23,465	24,024	23,564	22,544
15–19	10,986	12,036	12,337	12,086	10,626	11,374	11,639	11,434	21,612	23,410	23,977	23,520
20–24	10,234	10,937	11,987	12,287	10,354	10,597	11,348	11,617	20,588	21,534	23,335	23,904
25–29	11,003	10,181	10,886	11,932	11,053	10,317	10,566	11,319	22,056	20,498	21,452	23,251
30–34	10,298	10,943	10,132	10,834	10,227	11,004	10,280	10,533	20,525	21,948	20,412	21,367
35–39	9,664	10,229	10,880	10,073	9,488	10,169	10,952	10,238	19,153	20,397	21,832	20,311
40–44	8,614	9,571	10,143	10,788	8,489	9,412	10,100	10,888	17,103	18,983	20,243	21,677
45–49	7,279	8,478	9,437	10,000	7,254	8,385	9,315	10,010	14,532	16,863	18,751	20,010
50–54	6,071	7,085	8,273	9,208	5,895	7,116	8,250	9,185	11,966	14,201	16,523	18,394
55–59	4,554	5,800	6,793	7,931	4,190	5,723	6,939	8,073	8,744	11,523	13,732	16,004
60–64	3,030	4,224	5,404	6,329	3,241	3,998	5,498	6,702	6,271	8,222	10,902	13,031
65–69	2,303	2,682	3,764	4,816	2,555	2,994	3,734	5,179	4,858	5,677	7,497	9,995
70–74	1,585	1,890	2,218	3,113	1,992	2,226	2,654	3,356	3,577	4,116	4,872	6,469
75–79	872	1,152	1,384	1,625	1,175	1,567	1,800	2,195	2,047	2,719	3,184	3,820
80–84	498	522	690	829	685	779	1,083	1,288	1,183	1,301	1,773	2,118
85–89	189	221	225	298	264	347	420	615	453	569	645	913
90–94	66	55	59	60	111	92	132	171	177	147	191	232
95–99	34	11	8	9	65	24	22	35	98	35	30	43
100+	3	6	5	5	6	15	16	18	10	20	21	23
Total	**123,818**	**132,272**	**140,425**	**147,530**	**122,141**	**130,404**	**138,758**	**146,583**	**245,959**	**262,677**	**279,183**	**294,113**

Appendix 12. Projected Indonesian Population, 2010–2025 (in thousands) - High Fertility Scenario

Age group	Male				Female				Male + Female			
	2010	2015	2020	2025	2010	2015	2020	2025	2010	2015	2020	2025
0	2,339	2,504	2,511	2,516	2,213	2,393	2,398	2,402	4,552	4,896	4,910	4,918
1–4	9,731	9,293	9,947	9,958	9,189	8,802	9,526	9,555	18,920	18,096	19,473	19,513
5–9	12,393	12,136	11,591	12,406	11,674	11,463	10,985	11,891	24,067	23,599	22,576	24,297
10–14	12,071	12,367	12,115	11,570	11,394	11,657	11,449	10,973	23,465	24,024	23,564	22,544
15–19	10,986	12,036	12,337	12,086	10,626	11,374	11,639	11,434	21,612	23,410	23,977	23,520
20–24	10,234	10,937	11,987	12,287	10,354	10,597	11,348	11,617	20,588	21,534	23,335	23,904
25–29	11,003	10,181	10,886	11,932	11,053	10,317	10,566	11,319	22,056	20,498	21,452	23,251
30–34	10,298	10,943	10,132	10,834	10,227	11,004	10,280	10,533	20,525	21,948	20,412	21,367
35–39	9,664	10,229	10,880	10,073	9,488	10,169	10,952	10,238	19,153	20,397	21,832	20,311
40–44	8,614	9,571	10,143	10,788	8,489	9,412	10,100	10,888	17,103	18,983	20,243	21,677
45–49	7,279	8,478	9,437	10,000	7,254	8,385	9,315	10,010	14,532	16,863	18,751	20,010
50–54	6,071	7,085	8,273	9,208	5,895	7,116	8,250	9,185	11,966	14,201	16,523	18,394
55–59	4,554	5,800	6,793	7,931	4,190	5,723	6,939	8,073	8,744	11,523	13,732	16,004
60–64	3,030	4,224	5,404	6,329	3,241	3,998	5,498	6,702	6,271	8,222	10,902	13,031
65–69	2,303	2,682	3,764	4,816	2,555	2,994	3,734	5,179	4,858	5,677	7,497	9,995
70–74	1,585	1,890	2,218	3,113	1,992	2,226	2,654	3,356	3,577	4,116	4,872	6,469
75–79	872	1,152	1,384	1,625	1,175	1,567	1,800	2,195	2,047	2,719	3,184	3,820
80–84	498	522	690	829	685	779	1,083	1,288	1,183	1,301	1,773	2,118
85–89	189	221	225	298	264	347	420	615	453	569	645	913
90–94	66	55	59	60	111	92	132	171	177	147	191	232
95–99	34	11	8	9	65	24	22	35	98	35	30	43
100+	3	6	5	5	6	15	16	18	10	20	21	23
Total	**123,818**	**132,324**	**140,790**	**148,674**	**122,141**	**130,454**	**139,107**	**147,680**	**245,959**	**262,779**	**279,896**	**296,353**

Appendix 13. Chronic Disease Rates by Age Group

Age groups	Prevalence of chronic diseases (%)					
	Hypertension	Diabetes	Stroke	Cardiac	Cancer	Total
0–4	0.00	0.08	0.00	0.21	0.06	0.32
5–9	0.00	0.05	0.00	0.23	0.09	0.35
10–14	0.00	0.08	0.00	0.26	0.11	0.43
15–19	0.36	0.09	0.09	0.30	0.22	0.97
20–24	0.95	0.12	0.10	0.39	0.29	1.67
25–29	1.74	0.17	0.15	0.46	0.35	2.65
30–34	3.27	0.29	0.18	0.62	0.49	4.48
35–39	5.30	0.50	0.24	0.95	0.69	7.05
40–44	8.02	1.10	0.38	1.29	0.81	10.38
45–49	10.90	1.69	0.66	1.88	0.87	13.89
50–54	14.73	2.61	1.02	2.42	1.03	18.50
55–59	16.72	3.23	1.41	2.89	1.02	21.18
60–64	20.38	3.53	2.00	3.27	0.94	24.89
65–69	23.40	3.20	2.66	4.21	0.99	27.89
70–74	25.34	2.93	2.95	3.76	1.08	29.45
75+	25.58	2.64	3.26	3.98	1.15	29.85
Total	**4.45**	**0.66**	**0.35**	**0.88**	**0.42**	**5.84**

Data source: Calculated from 2007 Riskesdas

Appendix 14. Chronic Disease Rates, including Morbidity by Age Group and Sex

Age group	Chronic disease rate (%)		
	Male	Female	Male + Female
0–4	0.35	0.29	0.32
5–9	0.35	0.35	0.35
10–14	0.43	0.43	0.43
15–19	0.88	1.07	0.97
20–24	1.31	1.99	1.67
25–29	2.13	3.12	2.65
30–34	3.55	5.34	4.48
35–39	5.21	8.85	7.05
40–44	7.77	13.01	10.38
45–49	10.79	17.15	13.89
50–54	14.70	22.78	18.50
55–59	17.90	25.18	21.18
60–64	21.71	28.40	24.89
65–69	24.56	31.57	27.89
70–74	26.43	32.62	29.45
75+	27.96	31.64	29.85
Total	**4.88**	**6.82**	**5.84**

Data source: Calculated from 2007 Riskesdas

Appendix 15. Percentage of Change in Utilisation between 2010 and 2025, Attributable to Demographic, Insurance Subscription Rate and Chronic Disease Rate

Age group	Demographic effect (a)			Insurance effect (b)			Chronic disease effect		
	Male	Female	Male + Female	Male	Female	Male + Female	Male	Female	Male + Female
0–4	-14.0	-12.7	-13.4	5.8	7.1	6.4	0.1	0.1	0.1
5–9	-4.8	-3.2	-4.0	7.3	9.2	8.2	0.3	0.2	0.2
10–14	-4.1	-3.7	-3.9	8.0	9.9	9.0	0.5	0.4	0.5
15–19	10.0	7.6	8.8	9.9	12.4	11.2	1.7	1.3	1.5
20–24	20.1	12.2	15.8	11.2	12.9	12.1	2.6	2.0	2.3
25–29	8.4	2.4	5.3	9.9	11.0	10.5	3.7	2.6	3.0
30–34	5.2	3.0	4.1	8.9	10.5	9.7	5.8	4.6	5.1
35–39	4.2	7.9	6.0	8.3	10.1	9.2	7.6	7.1	7.4
40–44	25.2	28.3	26.7	9.3	11.7	10.5	9.9	8.5	9.1
45–49	37.4	38.0	37.7	10.0	12.3	11.2	12.1	9.7	10.8
50–54	51.7	55.8	53.7	10.9	13.6	12.2	12.5	8.9	10.6
55–59	74.1	92.7	83.2	12.4	16.1	14.2	10.5	4.8	7.6
60–64	108.9	106.8	107.8	14.7	17.0	15.9	7.6	3.3	5.3
65–69	109.1	102.7	105.7	13.3	16.2	14.9	8.1	4.5	6.2
70–74	96.4	68.5	80.8	13.0	13.8	13.5	10.1	8.8	9.4
75+	70.6	88.3	80.8	11.4	16.5	14.3	20.5	7.4	13.1
All Ages	**24.4**	**26.9**	**25.7**	**9.3**	**11.6**	**10.5**	**5.3**	**4.1**	**4.7**